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STOCHASTIC MODELING AS A MEANS OF AUTOMATIC SPEECH  
RECOGNITION

CARNEGIE-MELLON UNIVERSITY

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STOCHASTIC MODELING AS A MEANS OF  
AUTOMATIC SPEECH RECOGNITION

James R. Baker

April 1975

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## Block 20/Abstract

The DRAGON speech recognition system models the knowledge sources as probabilistic functions of Markov processes. The assumption of the Markov property allows the use of an optimal search strategy. The DRAGON system finds the sequence  $x[1:T]$  which maximizes the above probability, as given by the Markov model. In effect, the system searches all possible sentences in the grammar, all possible pronunciations of each sentence, and all possible dynamic time warpings of each such phonetic string to best fit it to the acoustic observations. This optimal search is carried out by the procedure expressed in equations (1) and (2).

$$(1) \gamma(t,j) = \text{Max}_i \{ \gamma(t-1,i) \text{Pr}(X(t)=j \mid X(t-1)=i, A,L,P,S) \\ \text{Pr}(Y(t)=y(t) \mid X(t-1)=i, X(t)=j, A,L,P,S) \}$$

Let  $l(t,j)$  be any value of  $i$  for which the above maximum is achieved.

$$(2) x(t) = l(t+1, x(t+1))$$

The use of a general theoretical framework, with an explicit representation for the solution process, greatly simplifies the speech recognition system. Equations (1) and (2) represent the entire recognition process. Despite its simplicity the system can, to some degree, use knowledge from each of the domains  $A, L, P$ , and  $S$ .

A simplified implementation of the DRAGON system has been developed using knowledge  $A$  and  $L$ , and some of the knowledge from  $S$ . This implementation has been tested on 102 utterances from 5 interactive computer tasks. The size of the integrated Markov network representing the knowledge sources is 410, 702, 916, 498, and 2356 states, respectively, for the 5 tasks whose vocabulary sizes are 24, 66, 37, 28, and 194 words, respectively, and which have grammars of varying degrees of complexity. The time required for recognition of an utterance is proportional to the length of the utterance and is given approximately by the expression (recognition time) = (utterance length)(20.9 + .067(net size)). Since a complete optimal search is performed, the recognition time is independent of the amount of noise in the signal or the number of errors in intermediate recognition decisions. The system correctly recognized 49% of the utterances and correctly identified 83% of the 578 words.

STOCHASTIC MODELING AS A MEANS OF  
AUTOMATIC SPEECH RECOGNITION

James K. Baker

April 1975

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## STOCHASTIC MODELING AS A MEANS OF AUTOMATIC SPEECH RECOGNITION

James K. Baker  
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Automatic recognition of continuous speech involves estimation of a sequence  $X(1), X(2), X(3), \dots, X(T)$  which is not directly observed (such as the words of a spoken utterance), based on a sequence  $Y(1), Y(2), Y(3), \dots, Y(T)$  of related observations (such as the sequence of acoustic parameter values) and a variety of sources of knowledge. Formally, we wish to find the sequence  $x[1:T]$  which maximizes the *a posteriori* probability  $\Pr( X[1:T]=x[1:T] \mid Y[1:T]=y[1:T], A, L, P, S )$ , where  $A, L, P, S$  represent the acoustic-phonetic, lexical, phonological, and syntactic-semantic knowledge. A speech recognition system must attempt to approximate a solution to this problem, whether or not the system uses a formal stochastic model.

The DRAGON speech recognition system models the knowledge sources as probabilistic functions of Markov processes. The assumption of the Markov property allows the use of an optimal search strategy. The DRAGON system finds the sequence  $x[1:T]$  which maximizes the above probability, as given by the Markov model. In effect, the system searches all possible sentences in the grammar, all possible pronunciations of each sentence, and all possible dynamic time warpings of each such phonetic string to best fit it to the acoustic observations. This optimal search is carried out by the procedure expressed in equations (1) and (2).

$$(1) \quad \gamma(t,j) = \text{Max}_i \{ \gamma(t-1,i) \Pr( X(t)=j \mid X(t-1)=i, A,L,P,S ) \\ \Pr( Y(t)=y(t) \mid X(t-1)=i, X(t)=j, A,L,P,S ) \}$$

Let  $l(t,j)$  be any value of  $i$  for which the above maximum is achieved.

$$(2) \quad x(t) = l(t+1, x(t+1))$$

The use of a general theoretical framework, with an explicit representation for the solution process, greatly simplifies the speech recognition system. Equations (1) and (2) represent the entire recognition process. Despite its simplicity the system can, to some degree, use knowledge from each of the domains  $A, L, P$ , and  $S$ .

A simplified implementation of the DRAGON system has been developed using knowledge  $A$  and  $L$ , and some of the knowledge from  $S$ . This implementation has been tested on 102 utterances from 5 interactive computer tasks. The size of the integrated Markov network representing the knowledge sources is 410, 702, 916, 498, and 2356 states, respectively, for the 5 tasks whose vocabulary sizes are 24, 66, 37, 28, and 194 words, respectively, and which have grammars of varying degrees of complexity. The time required for recognition of an utterance is proportional to the length of the utterance and is given approximately by the expression (recognition time) = (utt length)(20.9 + .067(nct size)). Since a complete optimal search is performed, the recognition time is independent of the amount of noise in the signal or the number of errors in intermediate recognition decisions. The system correctly recognized 49% of the utterances and correctly identified 83% of the 578 words.

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## INTRODUCTION

Speech recognition, a task which humans do efficiently and well, is very difficult to do by automatic procedures. There is a great deal of ambiguity in the actual acoustic signal—ambiguity which can be resolved only by applying other sources of knowledge in addition to the acoustic signal([A1], [R7], [N2]). In recent years much research has been devoted to developing the other sources of knowledge that are available in analyzing speech which is restricted to a specialized domain of discourse([R4], [R5], [T1], [D1], [P2], [W3], [F2], [B6], [W1], [L1], [J3]). In such a specialized domain there is generally a restricted vocabulary, so one source of knowledge is the lexical knowledge. The utterances are constrained to be grammatical and sometimes the grammar is a special restricted one, so there is syntactic knowledge. In some of the systems the specialized domain is an interactive task with the computer as a participant. Thus there is an operational definition of whether an utterance is "meaningful" (that is, can the computer interpret the utterance in relation to the interactive task), and therefore there is a kind of semantic knowledge([R6]).

In order to apply these sources of knowledge in speech recognition, it is necessary to represent this knowledge in a form that can be compared with the acoustic observations. There are two operations which are essential in any speech recognition system: searching and matching. Suppose one knowledge source, such as syntax, hypothesizes a word or a sequence of words. This hypothesis can only be verified by matching the words with the events observed by the other sources of knowledge, such as the actual acoustic signal. A matching procedure is needed to evaluate any particular hypothesis. A searching procedure is needed to explore the space of possible hypotheses.

## SEARCHING AND MATCHING IN SPEECH RECOGNITION SYSTEMS

The various speech recognition systems which have been developed use a great variety of searching and matching procedures and employ them in many different ways. The **DRAGON** speech recognition system, the subject of this thesis, is based on a systematic use of a particular abstract model to represent many of the sources of knowledge needed for speech recognition. This

uniformity of representation then allows a powerful general searching/matching technique to be applied to the speech recognition system as a whole. First let's consider some of the ways in which searching and matching procedures are used in other speech recognition systems.

The HEARSAY I system ([E2], [R3], [R4], [R5]) employs a hypothesize and test paradigm. There is a separate programming module for each source of knowledge which is represented. Each module is responsible for generating hypotheses based on its own internal knowledge. Each hypothesis is then verified by each of the modules (that is, each module matches the hypothesis against its own knowledge) and a combined rating is computed. The modules communicate with each other primarily by stating hypotheses about the sequence of words and each module has its own matching procedures for relating such "word-level" hypotheses to its own specialized knowledge. The search strategy is basically a best-first tree search. Words are hypothesized proceeding left-to-right in the utterance. At any point in the analysis new hypotheses are generated which are extensions of the best partial sequence of words obtain so far in the analysis. On the next round of the analysis, either the best such extension becomes the best partial sequence or, if all such extensions get sufficiently low ratings, a previous partial sequence (which had been the second best partial sequence) is reactivated.

In the HEARSAY II system ([L2]) the matching and search mechanisms are much more general and flexible. Hypotheses are not restricted to the word level, but instead are organized into an indefinite number of levels ranging from sub-phonetic acoustic segments to semantics and pragmatics. There are a large number of independent knowledge source modules. Each knowledge source repeatedly applies matching procedures to compare the data structure of existing hypotheses with its internal knowledge base. Whenever a match is found the knowledge source takes the appropriate action to add an hypothesis or otherwise modify the data structure. The search strategy consists of scheduling which knowledge sources get activated and in what order, based on a variety of scores and ratings for the hypotheses that are in the data structure at a given time.

In the Automatic Recognition of Continuous Speech (ARCS) systems ([D1], [T1], [T2], [T3], [P1], [P2], [R1]) a variety of tests are applied to the acoustic signal to derive a (noisy) phonetic

string and there is a language model for generating sequences of words. The conversion of the noisy phonetic string to an orthographic string is then performed by searching and matching procedures. For each word there is a network representing all permitted pronunciations of the word. The conditional probability of a particular word producing a given phonetic string can be computed explicitly, and is used to measure the degree of match. The search procedure is a best-first tree search implemented by a sequential decoding algorithm. Earlier versions of the ARCS system had the same general structure, but performed the matching at the phonetic level rather than at the word level.

The knowledge sources in the SPEECHLIS system ([B7], [N1], [R9], [W2], [W3]) represent their information in lattice structures which show all the alternatives at any point in time. The word-lattice is generated by matching each lexical item with the entries in the segment lattice. A semantic component searches the word lattice to develop "theories" of semantically related words. The semantic component continues to work on the theories with the greatest likelihood scores. When the semantics component can add no more words to a theory, the theory is passed to a syntax component which performs a parse and fills in any gaps.

The CASPER system ([F2], [K1]) performs a match between lexical items and a noisy phonetic sequence by using multiple dictionary entries, phonological rules embedded in the dictionary, and a "degarbling" procedure. The search is controlled by an augmented context-free grammar which performs a left-to-right, bottom-up parse.

The Vocal Data Management System ([B6], [R8]) developed at SDC employs a strategy of "Predictive Linguistic Constraints." The parser attempts to predict phrases based on a simple user model, thematic patterning, and grammatical and semantic constraints. Fixed directional parsing is replaced by a more general approach so that processing may be initiated at any point in the utterance. Lexical items are matched against the acoustic-phonetic data by a word mapper and a syllable mapper. The word mapper handles alternate pronunciations of a word, decides likely times for syllable boundaries, and checks for co-articulation effects across syllable boundaries. The syllable mapper compares a syllable candidate with the sequence of acoustic parameters.

The SRI Speech Understanding System ([P3], [P4], [W1]) uses a special "word function" for

each item in the lexicon. Each word function consists of a series of Fortran subroutines that look for a match between its particular word and data from a variety of sources based on parameters extracted from the acoustic signal. The parser executes a top-down, "best-first" strategy. In addition to its parsing function, it calls on the other components and coordinates information among them.

The Univac Speech Understanding System ([L1]) uses a prosodically-guided strategy. Prosodic features are used to break sentences into phrases, locate the stressed syllables within those phrases, and guide procedures for both phone classification and higher level linguistic analysis. This strategy requires a search procedure which is able to initiate processing at any point in the utterance as indicated by the prosodic features. Specific search and matching procedures have not yet been implemented for this system.

The speech recognition system being developed at the IBM Watson Research Center ([B1], [J3]) is based on a linguistic sequential decoder. The decoder consists of four major subparts: 1) a statistical model of the language, 2) a phonemic dictionary and statistical phonological rules, 3) a phonetic matching algorithm, 4) word level search control. The search procedure is a stack decoding algorithm which seeks that word sequence which has the maximum *a posteriori* probability, conditional on the language and the observed acoustic sequence. Statistical matching is done between hypothesized words and a noisy phonetic string obtained by acoustical analyses.

Even these greatly simplified descriptions make it clear that there is a great variety of ways in which searching/matching strategies can be implemented. However, certain common features can be distinguished. Most of the systems perform matching only at one level. Generally the matching is between lexical items and a noisy phonetic string (ARCS, SPEECHLIS, CASPER, IBM-Watson). Thus for example, in these systems, words and phrases are not directly matched to the acoustics. For most of the systems, the search is controlled primarily at the word level (HEARSAY I, ARCS, SPEECHLIS, CASPER, SDC, SRI, IBM-Watson). Only two systems (ARCS, IBM-Watson) have explicit statistical models from which to derive matching scores.

In addition to the general purpose searching/matching which is usually used in transforming a noisy phonetic string to a word string, several specialized procedures are used. SDC has a mapping

between syllables and acoustic parameters. SRI matches words directly with acoustics. The early ARCS system matched the language directly onto the noisy phonetic string. The segment data in the SPEECH-15 system is a lattice of alternatives, so matching even a single lexical item involves a small lattice search. Each of the modules in the HEARSAY systems includes specialized matching procedures.

### FEATURES OF THE DRAGON SYSTEM

The fundamental idea behind the **DRAGON** system is that each of the knowledge sources can be represented by a single, general, abstract model. Then powerful general search/match algorithms can be employed without worrying about all the special characteristics of each individual knowledge source. These special characteristics are not ignored, but they get incorporated into the data structures and not into the searching/matching procedures. The model which is used throughout the **DRAGON** system is that of a probabilistic function of a Markov process[B8].

The sequence of random variables  $Y(1), Y(2), Y(3), \dots, Y(T)$  is said to be a probabilistic function of a Markov process if there is a sequence of random variables  $X(1), X(2), X(3), \dots, X(T)$  such that the sequences of  $X$ 's and  $Y$ 's satisfy equations (5) and (6) of Chapter II. The techniques for analyzing such a system are described in Chapter II. The interpretation is that the  $Y$ 's are a sequence of random variables that we observe and which depend probabilistically on the  $X$ 's which we do not observe. We wish to make inferences about the values of the  $X$ 's from the observed values of the  $Y$ 's. Chapter III describes how the knowledge sources in a speech recognition system can be represented in terms of this type of model. Chapter IV describes a simplified implementation of these ideas. Performance results are given which show that even this greatly simplified implementation is a complete and powerful speech recognition system.

The important features of the **DRAGON** system are:

- 1) Generative form of model;
- 2) Hierarchical arrangement of knowledge sources;
- 3) Integrated network representation;



- 4) General theoretical framework;
- 5) Optimal stochastic search.

In comparing the features of different speech recognition systems, attention is often focused on the control structures and the methods of communication among the knowledge source modules. Thus a system might be characterized by whether the analysis proceeds top-down or bottom-up (or some mixture), whether there is a best-first tree search or some other control mechanism, and whether the analysis proceeds in a strict left-to-right fashion or can start at any point in the utterance. For several reasons, the **DRAGON** system cannot be easily characterized by these conventional dichotomies, so the discussion of them is postponed until the major features of the system are described.

#### (1) Generative form of the model

The generative form is a natural one for a probabilistic function of a Markov process. Generative rules are formulated as conditional probabilities. For example, if we know which phone occurs at a given time, vocal tract models allow us to predict the values of the acoustic parameters. That is, a conditional probability distribution is defined in acoustic parameter space. If we know which word occurs during a given segment of time, phonological rules allow us to estimate the probability of various phone sequences representing different pronunciations of the word. A statistical model for the errors of an automatic phone classifier allows us to calculate the probability of the classifier producing a specific sequence of labels, conditional on the true sequence of phones being a particular phone sequence. The grammar for a specific task domain produces a conditional probability distribution in the space of word sequences such that ungrammatical sequences have zero probability.

Each of the knowledge sources in the **DRAGON** system is represented in a generative form as a probabilistic function of a Markov process. However, Bayes' theorem allows the computation to be performed analytically. The model tells the conditional probability of producing a specific sequence of acoustic parameter values from a specific sequence of words. Applying Bayes'

theorem, we can compute the *a posteriori* probability of a sequence of words from the observed sequence of acoustic parameter values.

## (2) Hierarchical arrangement of knowledge sources

The sources of knowledge are organized into a hierarchy based on the following observation: The "higher" levels of a speech recognition system change state less frequently than the "lower" levels. Thus a single syntactic-semantic state corresponds to a sequence of several words; a single word corresponds to a sequence of several phones; and a phone corresponds to a sequence of acoustic parameter values. The hierarchy is not absolute—for example, syntax and semantics are together a single multi-level process—but it provides a convenient means for combining the Markov processes which represent the individual sources of knowledge.

To see how the knowledge can be represented as a hierarchy of generative models, let's consider a simplified example. Consider a language with only two sentences: "What did you see?" and "Where did you go?" At the word level this language can be represented by the network shown in Figure 1.

GRAMMAR NETWORK

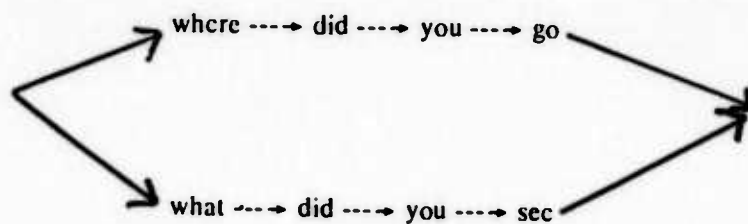


FIGURE 1

This model is generative in the sense that if we know a partial sequence of words (e.g. "What did") the model tells exactly which word can come next ("you"). But we do not directly observe the words (we only observe the associated acoustic events), so we must compute the *a posteriori* probability of any word sequence using the techniques of Chapter II.



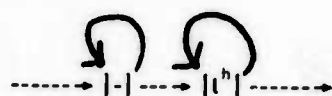
## WORD NETWORK



FIGURE 2

In the next lower level of the hierarchy we represent the relationship between the words and the phones. To keep the network simple, only a single pronunciation is represented for each word. For example, the network for "what" is shown in Figure 2. It is also possible to add another level to the hierarchy connecting the phones to the expected acoustic parameter values. The stop consonants and the diphthongs are broken up into several sub-phonemic segments. The network for [t<sup>h</sup>] is shown in Figure 3. The connection with acoustic parameters is then represented by a table giving the statistical distribution of parameter values for each type of segment. Phonological and acoustic-phonetic rules, which are omitted from this example, could be represented either at the broad phonetic level (such as, if the /t/ is flapped) or at the acoustic segment level (whether the /t/ is released and its degree of aspiration, if released).

## PHONE NETWORK



(where - represents the pause portion, and t<sup>h</sup> represents the release/aspiration)

FIGURE 3

The nodes in Figure 3 have arcs which point back to themselves because we are representing two processes which are asynchronous with respect to each other. That is, the acoustic parameters are measured at fixed time intervals (say once every 10 milliseconds), but each sub-phonemic acoustic segment lasts for an unknown period of time. So, if we time our stochastic process at one

step every 10 milliseconds, then the process may stay in the same state for several units of time, as indicated by an arc returning to the same node. A phone which consists of a single acoustic segment is represented by a phone network with a single node, but with a loop from the node back to itself, again indicating that the process may stay in this state for several units of time.

### (3) Integrated network representation

To describe a point in the hierarchical state space, we must describe its position in a network at each level of the hierarchy. For example, the description (1) "the pause segment" of (2) "the [t<sup>h</sup>]" of (3) "the word 'what'," describes a particular point in the hierarchical state space in our simple example. Since each of the networks is finite, it is possible to define a new network with a separate node for each point in the hierarchical space. In terms of the knowledge represented, this new network and the hierarchy of networks are equivalent. The change is primarily one of convenience. The integrated network representing our simplified example is shown in Figure 4.

#### INTEGRATED NETWORK

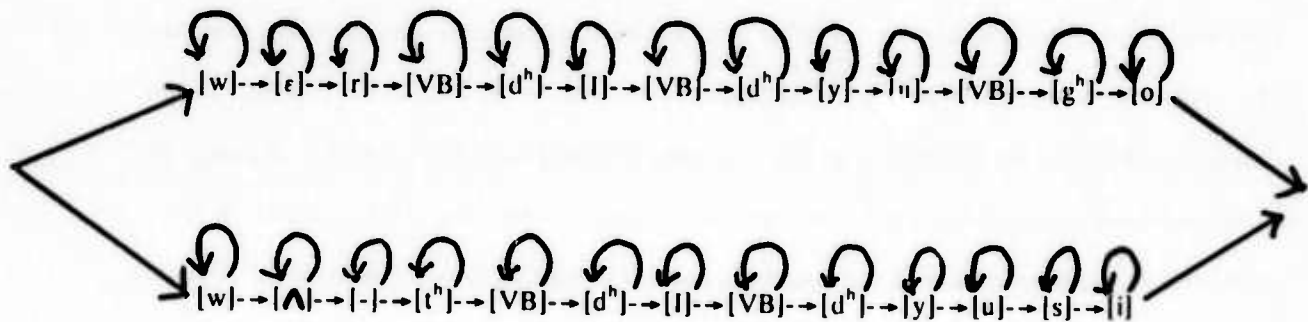


FIGURE 4

Actually it is possible to represent more knowledge in the integrated network than in the hierarchical system. For example, phonological rules which apply across word boundaries (such as the palatalization in the word pair "did.you") may be used to make modifications to the network. Note that the integrated network, because it is derived in a special way from a hierarchy, is very

sparse. In the example each node (except the end nodes) is connected to (has an arc pointed toward) only itself and one other node. Even with a more general language and networks representing phonological rules, almost any node that is not adjacent to a word boundary would be connected only to itself and one, two, or three other nodes. Thus, in a network with thousands of nodes, there are only two or three arcs per node (instead of the thousands which would be possible). This property of sparseness has implications for the implementation of the speech recognition system, as is discussed in Chapters II and IV.

The size of the integrated network for a given task depends on the vocabulary size, the complexity of the grammar, and on some of the details of the implementation. The five tasks discussed in Chapter IV have vocabulary sizes of 24, 66, 37, 28, and 194 words, respectively. The number of nodes in the integrated network is 410, 702, 916, 498, and 2356, respectively. Even the largest network is small enough so that the recognition system described in Chapter IV can keep all of its intermediate computational results in the computer's core memory with no need to use secondary storage.

Note that we go from a group of separate knowledge sources to an integrated network representation in essentially three steps. First, each knowledge source is represented as a probabilistic function of a Markov process. The details of this step are described in Chapter III. In this chapter the skeleton of the idea is exposed by way of the associated network. Second, the knowledge sources are arranged in a hierarchy. In a sense, it is this step which is crucial. It relies on the special relationships among the knowledge sources for speech recognition systems. It would not necessarily be applicable to knowledge sources for other problems even if the knowledge sources are representable as probabilistic functions of a Markov process. Third, the hierarchy of networks is converted into an equivalent single network (and the hierarchy of Markov processes is replaced by a single Markov process). Although this final step changes the apparent external structure of the system, it does not change the substance.

#### (4) General theoretical framework

As stated before, the **DRAGON** system relies throughout on a particular abstract model—that of a probabilistic function of a Markov process. A sequence of random variables  $Y(1)$ ,  $Y(2)$ ,

$Y(3), \dots, Y(T)$  is said to be a probabilistic function of the Markov process  $X(1), X(2), X(3), \dots, X(T)$  if these random sequences satisfy equations (5) and (6) of Chapter II. These equations may be paraphrased as requiring that, for any  $t$ ,  $X(t)$  depends only on  $X(t-1)$  and  $Y(t)$  depends only on  $X(t)$  and  $X(t-1)$ . Chapter III describes how various knowledge sources may be represented by such a model.

The formulas that the model produces are similar to the formulas used in other statistically based speech recognition systems (ARCS and IBM-Watson). In certain ways, either system can be considered as a special case of the other. The difference is more one of emphasis than one of kind. The emphasis in the **DRAGON** system is one of representing each of the knowledge sources in a uniform theoretical framework. Thus specialized procedures for handling the data for a particular knowledge source are avoided.

The only specialized procedures are those used in setting up the integrated network to represent the combined knowledge sources. In recognizing a particular utterance, the only procedure which is used is one which is based only on the general properties of a probabilistic function of a Markov process. For example, the type of specialized procedure which is absent is one which would take acoustic parameters and with a complicated set of rules, thresholds, and decisions produce a raw phonetic string intended to be as close as possible to a phonetic transcription of the utterance. As explained in Chapter III, if such a procedure is available, the **DRAGON** system can use the phonetic string which is produced. But on the other hand, if such a procedure is not used, the **DRAGON** system can operate directly on the acoustic parameters, since the acoustic-phonetic knowledge can be represented as a probabilistic function of a Markov process and be incorporated into the hierarchy.

#### (5) Optimal stochastic search

The Markov model used in the **DRAGON** system requires a finite state space. In that sense it is less general than the augmented network systems (SPEECHLIS, CASPER, SRI) and stack

decoding statistical systems (ARCS, IBM-Watson). However, a large finite network can represent most of the important information and some of the things which it cannot represent are irrelevant in a recognition problem in which the input is a noisy phonetic string with arbitrary insertions and deletions. The finite state space and the Markov model make possible the powerful algorithms which are described in Chapter II.

The search algorithm of the **DRAGON** system is unique in that rather than search a tree (the tree of possible word sequences) one branch at a time in some best-first or depth-first manner, it searches the entire space of all possible paths through its network. All paths of a given length are, in effect, searched in parallel. At the end of the analysis a path is obtained which is an optimum over all possible paths through the network. This path represents that interpretation of an utterance which, among all possible interpretations, best matches the given observed values of the acoustic parameters.

To search this entire space may seem to be drastic, but with the Markov model and the algorithms of Chapter II, it can be done very efficiently. These algorithms are not new. The inductive computation of the best partial sequence, as done by equation (18) of Chapter II, is an application of dynamic programming to the general network search problem([B9]). It corresponds to an algorithm used in communications and coding theory, known as the Viterbi algorithm([V1]). There are other algorithms for sequential decoding([F1], [J1], [J2]), which are also based on maximizing the *a posteriori* probability according to such a stochastic model, and several of them have been successfully applied to speech recognition (ARCS and IBM-Watson).

The number of computations required to search the space of all possible paths through the network is proportional to (the length of the utterance) times (the number of arcs in the network). For a given network, the computation time is linear in the length of the utterance and is independent of the amount of noise or the number of errors in any input string. This property is in sharp contrast to depth-first or best-first algorithms for which there is no effective upper bound for the amount of computation (except a search of the entire tree, one branch at a time). The sequential search algorithms do, in fact, occasionally need to be terminated before completion of the analysis because they exhaust the available time or storage.

On the other hand, although the Markov model permits a complete optimum search in a time that is linear in the length of the utterance, the proportionality factor is large, especially for large vocabularies. Many things could be done to reduce the computation time required by the **DRAGON** system, and they are an important and interesting area for future research, but in the work reported in this thesis there has been no attempt to minimize the computation time. Lowerre ([L3]) has rewritten the **DRAGON** program to execute much faster with no change in recognition results. The computation times given in Chapter IV, therefore, should be regarded as an upper bound on the amount of time required by the techniques presented in this thesis and as a demonstration that complete optimal search is not impossible.

The **DRAGON** system cannot be characterized as either top-down or bottom-up because it has aspects of both types of system. The models are given in a generative form, which is normal for top-down systems. However, by applying Bayes' formula the analysis proceeds in the analytic rather than the synthetic direction. But even more significant is the fact that the integrated representation makes it impossible to distinguish whether the acoustic knowledge is helping to direct the syntactic analysis, or if the syntactic knowledge is helping to direct the acoustic analysis. Instead of a system with separate components with specific feed-back and feed-forward mechanisms for transmitting information, the system is completely integrated.

The **DRAGON** system represents an extreme position in terms of its search strategy. Most systems use some form of best-first tree search with procedures for backtracking when the analysis requires it. By contrast, the **DRAGON** system uses a complete optimal search, which would be like a breadth-first tree search except the Markov model reduces the tree search to a much smaller network search.

The particular implementation which is discussed in Chapter IV is restricted to a strict left-to-right analysis, and the formulas in Chapters II and III have been expressed in that form. It would be possible to generalize this system to have the analysis proceed from any point in the utterance, but because there is already a complete optimal search, there is no advantage in doing so. It is not necessary to start the analysis at "islands of reliability" because any path which gives the correct interpretation of such an island is eventually considered in the optimal search (unlike a



best-first search in which analyzing unreliable data first can cause the correct interpretation of later reliable data never to be considered). Because the computation time is a linear function of the length of the utterance there is no computational advantage in breaking the utterance into several pieces.

The remainder of this thesis is divided into three chapters. Chapter II describes the abstract model which is used in the **DRAGON** system. In the **DRAGON** system each source of knowledge is represented as a probabilistic function of a Markov process([B8]). Chapter II presents the general mathematical properties for such systems, but omits the details which are specific to speech recognition. Chapter III presents techniques for representing the knowledge sources necessary for speech recognition. Sometimes several alternative techniques are described for representing a particular source of knowledge. Some of the representation techniques described in Chapter III are used in the simple implementation discussed in Chapter IV. Some of the other techniques have been tested in separate modules but not in a complete recognition system. Some of the techniques have not yet been tested. In particular, no attempt has been made to represent a semantic component or even to obtain a weighted probabilistic grammar. Chapter IV describes a speech recognition system, based on the general model of Chapter II, obtained by implementing some of the representation techniques presented in Chapter III. A summary is presented of recognition results for 102 utterances. The system correctly recognized 49% of the 102 utterances and correctly identified 83% of the 578 words.



## INTRODUCTION

The **DRAGON** speech recognition system utilizes the theory of a probabilistic function of a Markov process. In this chapter an introduction is given to the general theory. Chapter III explains how the knowledge sources in a speech recognition system can be represented.

Let  $Y(1), Y(2), Y(3), \dots, Y(T)$  be a sequence of random variables representing the external (acoustic) observations. Let  $X(1), X(2), X(3), \dots, X(T)$  be a sequence of random variables representing the internal states of a stochastic process such that the probability distributions of the  $Y$ 's depend on the values of the  $X$ 's, but the  $X$ 's are not directly observed. As a convenient abbreviation we use a bracket and colon notation to represent sequences. Thus,  $Y[1:T]$  represents  $Y(1), Y(2), Y(3), \dots, Y(T)$  and  $X[1:T]$  represents  $X(1), X(2), X(3), \dots, X(T)$ . Let  $y[1:T]$  be the observed sequence of values for the random variables  $Y[1:T]$ .

## GENERAL FORMULATION

We wish to make inferences about the sequence  $X[1:T]$  in light of the knowledge of  $y[1:T]$ . For example, we would like to know the conditional probability  $\text{PROB}(X(t)=j \mid Y[1:T]=y[1:T])$  for each  $t$  and  $j$  (the conditional probability of a specific internal state at a specific time, given the entire sequence of external observations). Assuming we have a model for speech production, we can evaluate the *a priori* probability  $\text{PROB}(X[1:T])$ . Assuming a model for the generation of acoustic events associated with a specific sequence of internal states, we can evaluate the conditional probability  $\text{PROB}(Y[1:t]=y[1:t] \mid X[1:T]=x[1:T])$  (That is, the model yields conditional probabilities of external observations, given the sequence of internal states). Thus we know the conditional probabilities in the generative or synthetic form.

We can compute the desired conditional probabilities using Bayes' formula

$$(1) \text{PROB}(X(t)=j \mid Y[1:T]=y[1:T])$$

$$= \text{PROB}(X(t)=j, Y[1:T]=y[1:T]) / \text{PROB}(Y[1:T]=y[1:T])$$

if we can evaluate the factors on the right hand side. The numerator is given by

$$(2) \text{PROB}(X(t)=j, Y[1:T]=y[1:T])$$

$$= \sum_{x[1:T], x(t)=j} \text{PROB}(X[1:T]=x[1:T], Y[1:T]=y[1:T])$$

$$= \sum_{x[1:T], x(t)=j} \text{PROB}(Y[1:T]=y[1:T] \mid X[1:T]=x[1:T]) \text{PROB}(X[1:T]=x[1:T])$$

where the sum is taken over all possible sequences  $x[1:T]$  subject to the restriction  $x(t)=j$ . (The joint probability of an internal sequence and an external sequence is the product of the *a priori* probability of the internal sequence and the conditional probability of the external sequence given by the model. The probability for the event  $X(t)=j$  is obtained by summing over all internal sequences which meet that restriction.) We can evaluate the *a priori* probability that  $Y[1:T]$  would be  $y[1:T]$  as

$$(3) \text{PROB}(Y[1:T]=y[1:T])$$

$$= \sum_{x[1:T]} \text{PROB}(Y[1:T]=y[1:T] \mid X[1:T]=x[1:T]) \text{PROB}(X[1:T]=x[1:T])$$

where the sum is taken over all possible sequences  $x[1:T]$ . (The total probability of an external sequence is the sum of its joint probability with all possible internal sequences.)

Therefore

$$(4) \text{PROB}(X(t)=j \mid Y[1:T]=y[1:T])$$

$$\begin{aligned} &= \text{PROB}(X(t)=j, Y[1:T]=y[1:T]) / \text{PROB}(Y[1:T]=y[1:T]) \\ &= \frac{\sum_{x[1:T], x(t)=j} \text{PROB}(Y[1:T]=y[1:T] \mid X[1:T]=x[1:T]) \text{PROB}(X[1:T]=x[1:T])}{\sum_{x[1:T]} \text{PROB}(Y[1:T]=y[1:T] \mid X[1:T]=x[1:T]) \text{PROB}(X[1:T]=x[1:T])} \end{aligned}$$

where the sum in the denominator is taken over all sequences  $x[1:T]$  and the sum in the numerator is taken over all such sequences subject to the restriction  $x(t)=j$ . (This is the probability of the internal event  $X(t)=j$  conditional on the observed external sequence, as desired.)

The derivation of equation (4) is just a standard application of Bayes' theorem. It represents a formal inversion of the conditional probabilities from the generative form to the analytic form. (Note: The word "analytic" is used here in a special sense. "Analytic" means "taking apart" as

opposed to "synthetic," "generative," or "putting together." In terms of our model, the generative form predicts the observations (Y's) in terms of the internal sequence (X's). The analytic form computes the *a posteriori* probability of the X's conditional on the observed Y's.) The speech-recognition knowledge sources provide the conditional probabilities in a generative form. They must be converted into an analytic form to make inferences about a particular utterance from the observed acoustics. However, the formal inversion formula given in equation (4) is not computationally practical since in general the set of all possible sequences  $x[1:T]$  is prohibitively large. It is necessary to apply the restrictions of a more specific model to obtain a computationally efficient formula.

### MARKOV MODEL

The DRAGON speech recognition system assumes that the sequences represent a probabilistic function of a Markov process[B8]. Specifically, it is assumed that the conditional probability that  $X(t)=j$  given  $X(t-1)$  is independent of  $t$  and of the values of  $X[1:t-2]$  and that the conditional probability that  $Y(t)=k$  given  $X(t)$  and  $X(t-1)$  is independent of  $t$  and of the values of any of the other X's and Y's. Let  $B = \{ b_{i,j,k} \}$  and  $A = \{ a_{i,j} \}$  be arrays such that

$$\begin{aligned} (5) \quad & \text{PROB}( Y(t)=y(t) \mid X[1:t]=x[1:t], Y[1:t-1]=y[1:t-1] ) \\ &= \text{PROB}( Y(t)=y(t) \mid X(t-1)=x(t-1), X(t)=x(t) ) \\ &= b_{x(t-1),x(t),y(t)} \end{aligned}$$

and

$$\begin{aligned} (6) \quad & \text{PROB}( X(t)=x(t) \mid X[1:t-1]=x[1:t-1] ) \\ &= \text{PROB}( X(t)=x(t) \mid X(t-1)=x(t-1) ) \\ &= a_{x(t-1),x(t)} \end{aligned}$$

This restriction to a Markov model is the fundamental assumption which allows the DRAGON system to be practical. In the Markov model the conditional probabilities depend only on  $X(t)$  and

$X(t-1)$  and not on the entire sequence  $X[1:T]$  as in equations (1) to (4). This specialization makes it possible to evaluate the desired conditional probabilities by an indirect but computationally efficient procedure.

The Markov assumption might be paraphrased by saying that the conditional probabilities are independent of context, but such a simple statement would be misleading. Since the state space of the Markov process for our speech recognition application has not yet been formulated, the assumption of the Markov properties should be regarded as a prescription to be followed in the formulation of the state space. Specifically, two situations which differ in "relevant" context must be assigned two separate states in the state space of the random variables  $X[1:T]$ . Then all "relevant" context is included in the state space description, and the conditional probabilities are indeed independent of further context. The fundamental assumption of the **DRAGON** system is that it is possible to meet this prescription and still have a state space of manageable size.

Under the assumptions of equations (5) and (6) we have

$$(7) \text{PROB}(X[1:s]=x[1:s]) = \text{PROB}(X(1)=x(1)) \left( \prod_{t=2,s} a_{x(t-1),x(t)} \right).$$

(The *a priori* probability of a given internal state sequence is the product of the transition probabilities for all the transitions in the sequence.) To simplify, add a special extra state to the Markov process; let  $x(0)$  be this special state and define  $a_{x(0),1} = \text{PROB}(X(1)=j)$ . Similar conventions are assumed throughout this thesis, unless specifically mentioned otherwise. Then

$$(8) \text{PROB}(X[1:s]=x[1:s]) = \prod_{t=1,s} a_{x(t-1),x(t)}$$

Also

$$(9) \text{PROB}(Y[1:s]=y[1:s] | X[1:s]=x[1:s]) = \prod_{t=1,s} b_{x(t-1),x(t),y(t)}$$

(the model-defined probability of an external sequence, conditional on the internal sequence)

where  $b_{x(t-1),k}$  is defined appropriately. Combining (8) and (9) yields

$$(10) \text{PROB}(X[1:s]=x[1:s], Y[1:s]=y[1:s]) = \prod_{t=1,s} a_{x(t-1),x(t)} b_{x(t-1),x(t),y(t)}$$

(the joint probability of an internal sequence and an external sequence as given by the Markov model).

To make possible the efficient computation of the sums in equations (3) and (4), we introduce the probabilities of partial sequences of states and observations ([B8]). Using (2) with  $t=T=s$  and using (10), we can set

$$(11) \alpha(s, x(s)) = \text{PROB}(X(s)=x(s), Y[1:s]=y[1:s])$$

$$= \sum_{x[1:s-1]} \prod_{t=1,s} a_{x(t-1), x(t)} b_{x(t-1), x(t), y(t)}$$

where the sum is over all possible sequences  $x[1:s-1]$ . (This is the joint probability of the partial external sequence, up to time  $s$ , and the event that the process is in state  $x(s)$  at time  $s$ .) Let

$$(12) \beta(s, x(s)) = \text{PROB}(X(s)=x(s), Y[s+1:T]=y[s+1:T])$$

$$= \sum_{x[s+1:T]} \prod_{t=s+1,T} a_{x(t-1), x(t)} b_{x(t-1), x(t), y(t)}$$

where the sum is over all possible sequences  $x[s+1:T]$ . (This is the joint probability of the partial external sequence from time  $s+1$  to the end, and the event that the process is in state  $x(s)$  at time  $s$ .) The benefit of introducing the functions  $\alpha$  and  $\beta$  is that the values of  $\alpha(s, j)$  for a given  $s$  can be computed from the values of  $\alpha(s-1, i)$ . Similarly,  $\beta$  for a given  $s$  can be computed from the values of  $\beta$  for  $s+1$ .

## RECOGNITION EQUATIONS

In fact

$$(13) \alpha(s, j) = \sum_i \alpha(s-1, i) a_{i,j} b_{i,j,y(s)}$$

(because every sequence  $x[1:s]$  must have  $x(s-1)=i$  for some  $i$ )

and

$$(14) \beta(s, j) = \sum_i \beta(s+1, i) a_{j,i} b_{j,i,y(s+1)}$$

But  $\alpha(T, j) = \text{PROB}(X(T)=j, Y[1:T]=y[1:T])$  hence

$$(15) \text{PROB}(Y|1:T=y|1:T) = \sum_i \alpha(T,i).$$

We can compute the conditional probability distribution for  $X(t)$

$$\begin{aligned} (16) \text{PROB}(X(t)=j \mid Y|1:T=y|1:T) \\ = \text{PROB}(X(t)=j, Y|1:T=y|1:T) / \text{PROB}(Y|1:T=y|1:T) \\ = \alpha(t,j)\beta(t,j) / \sum_i \alpha(t,i). \end{aligned}$$

In speech recognition problems, we usually want to know the particular sequence  $x|1:T$  which maximizes the joint probability  $\text{PROB}(X|1:T=x|1:T, Y|1:T=y|1:T)$ . Again, the problem can be solved by induction from partial sequences ([B9]). Let

$$(17) \gamma(t,j) = \text{Max}_{x|1:t-1} \text{PROB}(X|1:t-1=x|1:t-1, X(t)=j, Y|1:t=y|1:t)$$

Then  $\gamma$  may be computed by

$$(18) \gamma(t,j) = \text{Max}_i \gamma(t-1,i) a_{i,j} b_{i,j,y(t)}.$$

Notice that equation (18) is just like equation (13) except that Max has been substituted for  $\Sigma$ . It is convenient to save "back-pointers" while computing  $\gamma$ . Therefore, let  $l(t,j)$  be any value of  $i$  for which the maximum is achieved in equation (18). Then a sequence  $x|1:T$  for which  $\text{PROB}(X|1:T=x|1:T, Y|1:T=y|1:T)$  is maximized is obtained by

$$(19) x(T) = j, \text{ where } j \text{ is any index such that } \gamma(T,j) = \text{Max}_i \gamma(T,i)$$

and

$$(20) x(t) = l(t+1, x(t+1)), \quad t = T-1, T-2, \dots, 2, 1.$$

So far the analysis has assumed that the matrices  $A$  and  $B$  are fixed and known. However, if  $A$  and  $B$  are not known but must be estimated, then the  $\alpha$  and  $\beta$  computed above may be used to obtain a Bayesian *a posteriori* re-estimation of  $A$  and  $B$ . The matrix  $A$  is re-estimated by

$$(21) \hat{a}_{i,j} = \frac{\sum_{t=1, T-1} \text{PROB}(X(t)=i, X(t+1)=j \mid Y|1:T=y|1:T, \{a_{i,j}\}, \{b_{i,j,k}\})}{\sum_{t=1, T-1} \text{PROB}(X(t)=i \mid Y|1:T=y|1:T, \{a_{i,j}\}, \{b_{i,j,k}\})}$$



$$= \frac{\sum_{t=1, T-1} \alpha(t, i) a_{i,j} b_{i,j,y(t+1)} \beta(t+1, j)}{\sum_{t=1, T-1} \alpha(t, i) \beta(t, i)}$$

The matrix B is re-estimated by

$$(22) \hat{b}_{i,j,k} = \frac{\sum_{t=1, T-1; y(t+1)=k} \text{PROB}(X(t)=i, X(t+1)=j \mid Y[1:T]=y[1:T], \{a_{i,j}\}, \{b_{i,j,k}\})}{\sum_{t=1, T-1} \text{PROB}(X(t)=i, X(t+1)=j \mid Y[1:T]=y[1:T], \{a_{i,j}\}, \{b_{i,j,k}\})}$$

$$= \frac{\sum_{t=1, T-1; y(t+1)=k} \alpha(t, i) a_{i,j} b_{i,j,k} \beta(t+1, j)}{\sum_{t=1, T-1} \alpha(t, i) a_{i,j} b_{i,j,y(t+1)} \beta(t+1, j)}$$

In fact it can be shown ([B8]) that

$$(23) \text{PROB}(Y[1:T]=y[1:T] \mid \{\hat{a}_{i,j}\}, \{\hat{b}_{i,j,k}\}) \geq \text{PROB}(Y[1:T]=y[1:T] \mid \{a_{i,j}\}, \{b_{i,j,k}\}).$$

Thus, each time the re-estimation equations (21) and (22) are used, new matrices are obtained such that the estimated probability of the observations  $Y[1:T]=y[1:T]$  is non-decreasing. Since this estimated probability is a continuous function of the matrix entries (in fact, a polynomial with terms as given by equation (10)), and since the matrix entries are constrained to a compact set (because the entries are non-negative and the row sums are 1), this estimated probability must converge for any sequence of matrices obtained by repeated use of the re-estimation equations. Hence the re-estimation given by equations (21) and (22) may be used repeatedly in an attempt to obtain  $\{a_{i,j}\}$  and  $\{b_{i,j,k}\}$  which maximize  $\text{PROB}(Y[1:T]=y[1:T] \mid \{a_{i,j}\}, \{b_{i,j,k}\})$ . Thus we can obtain an approximation to maximum likelihood estimates for  $\{a_{i,j}\}$  and  $\{b_{i,j,k}\}$ .

In re-estimating the matrices A and B, the special structure of the speech recognition problem can be used to good advantage. Although it is convenient to use a single integrated model for the actual analysis and recognition of utterances, the re-estimation of the structural matrices can be performed separately for each of the levels in the hierarchy. Also note that any entry in A or B which is zero remains zero in the re-estimations of equations (21) and (22). Therefore we are able to maintain and utilize the sparseness of these matrices in the re-estimation process.



## INTRODUCTION

Each of the knowledge sources in a speech recognition system can be represented in terms of the general model of Chapter II. The total hierarchical system also fits such a model, and it is the total system to which the estimation procedures of Chapter II are applied. This chapter explains the representation of knowledge from each of the sources and their integration into the hierarchy.

## REPRESENTATION OF ACOUSTIC-PHONETIC KNOWLEDGE

There are several choices as to how to represent acoustic-phonetic knowledge. A decision must be made whether acoustic observations should be preprocessed by specialized procedures or whether the stochastic model should deal directly with the acoustic parameters. The representation problem is easier assuming specialized preprocessing, so consider this case first.

Assume that at each time  $t$  ( $1 \leq t \leq T$ ), an acoustic observation is made. Each such observation consists of a vector of values of a set of acoustic parameters, which in the stochastic model is represented by a vector-valued random variable  $Y(t)$ . There is a sequence of phones  $P[1:J]$  which is produced during the time interval  $1 \leq t \leq T$ . Assume that the phones occupy disjoint segments of time; that is, assume there is a sequence  $s_0 < s_1 < s_2 < s_3 < \dots < s_J$  such that  $P(j)$  lasts from observation  $Y(s_{j-1})$  through observation  $Y(s_j - 1)$ . (Set  $s_0 = 1$ ,  $s_J = T$ .)

Let  $p[1:J]$  be the actual sequence of phones in an utterance and let  $y[1:T]$  be the actual observed sequence of acoustic parameters. For convenience, also introduce a special initialization phone  $p(0)$  which is assigned a special value to allow the initial probabilities to have the same form as the transition probabilities later in the sequence. Since the actual times  $s_1, s_2, s_3, \dots, s_{J-1}$  are not known, it is necessary to associate each arbitrary segment of time with some phone. For each pair of times  $t_1$  and  $t_2$  let  $S(t_1, t_2)$  be that value of  $j$  for which the expression  $(\text{Min}(s_j, t_2) - \text{Max}(s_{j-1}, t_1))$  is maximized. (That is, we associate with the pair  $t_1$  and  $t_2$  the index of the phone segment which has the greatest interval in common with the interval from  $t_1$  to  $t_2$ .) If  $t_2 \leq 1$ , then set  $S(t_1, t_2) = 0$ .

The acoustic preprocessor tries to estimate a phonetic transcription from the acoustics alone. By looking for discontinuities or rapid changes in the acoustic parameters, the preprocessor divides

the sequence up into  $K$  phone-like segments  $Y[1:t_1-1], Y[t_1:t_2-1], Y[t_2:t_3-1], \dots, Y[t_{K-1}:t_K-1]$ . Then an attempt is made to classify each segment  $Y[t_{k-1}:t_k-1]$  using some form of pattern recognition procedure. Let  $t_0 < t_1 < t_2 < \dots < t_K$  be the segment boundary times as decided by the preprocessor and introduce the random variable  $D(t)$  which is 1 if there exists a  $k$  such that  $t_k = t$  and is 0 otherwise. Let  $F(k)$  be the label assigned by the preprocessor to the segment  $Y[t_{k-1}:t_k-1]$ . (For completeness, set  $t_k = t_0 = 1$  for  $k < 0$ , and  $t_k = t_K = T$  for  $k > K$ .)

With some pattern matching procedures it is possible to directly estimate conditional probabilities. When using such a procedure, let

$$(1) B(p,k) = \text{PROB}(Y[t_{k-1}:t_k-1]=y[t_{k-1}:t_k-1] \mid P(S(t_{k-1},t_k)=p))$$

(the probability that segment  $k$  corresponds to phone  $p$  as estimated by the pattern matching procedure). On the other hand, the pattern matching procedure might yield only a label  $F(k)$  representing a best guess as to the underlying phone. In such a case, it is necessary to estimate the conditional probabilities from statistics of performance of the pattern matcher on hand-labeled data. Let  $f[1:K]$  represent the actual sequence of labels generated by the pattern recognizer for the utterance being considered. Then set:

$$(2) B(p,k) = \text{PROB}(F(k)=f(k) \mid P(S(t_{k-1},t_k)=p)).$$

(The probability that segment  $k$  corresponds to phone  $p$  is estimated as the probability that a segment labeled  $f(k)$  corresponds to phone  $p$ .) where the conditional probability is estimated by the frequency of such events in a set of training utterances.

In addition to estimating the probability of substitutions or confusions, it is necessary to estimate the probability of the preprocessor producing either too many or too few segments. The probability of such events may be estimated from their frequency of occurrence in a set of training utterances. Let

$$(3) E(p_1,p_2,n) = \text{PROB}(D(t_{k-2})=D(t_{k-1})=D(t_k)=1, D[t_{k-2}+1:t_{k-1}-1]=0, D[t_{k-1}+1:t_k-1]=0 \mid P(S(t_{k-2},t_{k-1}))=p_1, P(S(t_{k-1},t_k))=p_2, S(t_{k-1},t_k)=S(t_{k-2},t_{k-1})+n).$$

(The probability that the segmenter finds one boundary between a segment corresponding to phone  $p_1$  and a segment corresponding to phone  $p_2$ , given that the phones are actually  $n$  positions apart in the sequence of phones.) If the acoustic preprocessor is reliable, then  $E(p_1, p_2, n)$  should be small, except for  $n=1$  and should be negligible for  $n>2$ . In an implementation of the **DRAGON** system which uses an acoustic preprocessor, it has arbitrarily been assumed that  $E(p_1, p_2, n) = 0$  for  $n>4$ . Note that  $E(p_1, p_2, 0)$  is undefined and meaningless unless  $p_1 = p_2$ .

We can now estimate the conditional probability of the sequence  $Y[1:T]$  given the sequence  $P[1:J]$ .

$$(4) \text{PROB}(Y[1:T]=y[1:T] \mid P[0:J]=p[0:J])$$

$$= \sum_{n[1:K], z(K)=J} B(p(z(k)), k) E(p(z(k-1)), p(z(k)), n(k)),$$

where  $z(k) = \sum_{i=1,k} n(i)$  and the sum is taken over all sequences  $n[1:K]$  such that  $z(K) = J$ . (By convention  $z(0) = 0$ .) This equation is a special case of equation (9) of Chapter II.

In order to apply the theory of a probabilistic function of a Markov process, it is necessary to specify the transition probabilities for the phone sequence  $P[1:J]$ . It is the task of the other sources of knowledge to specify these probabilities. Phonological rules may be represented either directly or indirectly in the estimates of  $E(p_1, p_2, n)$  and  $B(p, k)$ , but all higher levels of the hierarchy deal only with the sequence  $P[1:J]$  and are insulated from the acoustics  $Y[1:T]$  or the labels  $F[1:K]$ .

Even if no special preprocessing is assumed, it is not difficult to represent the acoustic-phonetic knowledge, but there is a penalty of extra computation. Direct estimation of the conditional probability  $\text{PROB}(Y[1:T]=y[1:T] \mid P[1:J]=p[1:J])$  is similar to the problem of machine-aided segmentation and labeling ([B2]). Similar algorithms have also been used for word-spotting in continuous speech ([B4], [B11]) and for isolated word recognition ([11]). The essential idea is an elastic change of the time scale to optimally match a sequence of acoustic observations to a sequence of prototypes.

To relate the phones to the acoustic observations requires knowledge of the acoustic phenomena which are expected with each phone. In line with the probabilistic approach, each phone is assumed to be associated with a stochastic process which produces acoustic parameter values for each instance of the phone. The statistical properties of the stochastic process associated with any particular phone are to be estimated from occurrences of the phone in a set of training utterances which have already been segmented and labeled.

Each acoustic observation is to take a value from a finite set  $D$ . Assume that for each phone  $p$  there is a positive-integer-valued random variable  $Z_p$  and a family of random variables  $X_p(1), X_p(2), X_p(3), \dots, X_p(Z_p)$  with values in  $D$ . Let  $f_{p,n}$  be the conditional probability function

$$(5) f_{p,n}(x(1), x(2), x(3), \dots, x(n)) = \text{PROB}(X_p[1:n] = x[1:n] \mid Z_p = n).$$

Let  $g_p(n) = \text{PROB}(Z_p = n)$ . The interpretation is that  $Z_p$  is the duration of an instance of phone  $p$  and  $X_p[1:z_p]$  are the acoustic observations made during that instance of  $p$ .

Let  $y[1:T]$  be the sequence of observations made for the utterance being analyzed. Let  $p[1:J]$  be the sequence of phones in the utterance. Let  $U[1:J]$  be the sequence of boundary times for the phones. That is,  $U(1) < U(2) < U(3) < \dots < U(J)$  and, for each  $j$ ,  $P(j)$  lasts from observation  $Y(U(j-1))$  to observation  $Y(U(j)-1)$ . Suppose a set of observations  $Y[1:T]$  and times  $U[1:J]$  are produced by applying in succession the stochastic processes for each of the phones  $P(1)$  through  $P(J)$  and concatenating the observations, the individual processes being independent. Then the probability of producing the observed sequence is

$$(6) \text{PROB}(Y[1:T] = y[1:T], U[1:J] = u[1:J] \mid P[1:J] = p[1:J]) \\ = \prod_{j=1}^J (f_{p(j), u(j)-u(j-1)}(y[u(j-1):u(j)-1]) g_{p(j)}(u(j)-u(j-1))).$$

The segmentation and labeling problem consists of finding the correct set of values for the sequence  $U[1:J]$ . Representing the acoustic-phonetic knowledge in a speech recognition system is similar, except the transitions among the phones are determined by probabilities specified by other sources of knowledge rather than being a known sequence.

Note that our model is such that for a given  $k$  and  $u[k:J]$  we can evaluate

$$(8) \text{PROB}(Y[u(k):T]=y[u(k):T], U[k:J]=u[k:J] \mid P[1:J]=p[1:J]) \\ = \prod_{j=k+1}^J (f_{p(j), u(j)-u(j-1)}(y[u(j-1):u(j)-1]) g_{p(j)}(u(j)-u(j-1)));$$

that is, the probability does not depend on  $U[1:k-1]$ . The process is an example of a probabilistic function of a Markov process with the vector  $(k, U(k))$  being the state variable of the Markov process. The problem of machine-aided labeling can be solved by the techniques of Chapter II.

Introduce the function

$$(9) \gamma_1(j, t) = \text{Max}_{u[1:J], u(j)=t} (\text{PROB}(Y[1:t-1]=y[1:t-1], U[1:j]=u[1:j] \mid P[1:J]=p[1:J])).$$

That is,  $\gamma_1(j, t)$  is the probability of the best sequence leading up to the state  $(j, t)$ . The function  $\gamma_1$  may be calculated according to equation (18) of Chapter II. Thus

$$(10) \gamma_1(j, t) = \text{Max}_k (\gamma_1(j-1, t-k) f_{p(j), k}(y[t-k:t-1]) g_{p(j)}(k)).$$

Let  $K(j, t)$  be any value of  $k$  for which this maximum is achieved. Then after  $\gamma_1$  and  $K(j, t)$  have been calculated for all  $j$  and  $t$ , the best sequence  $u[1:J]$  is obtained by

$$(11) u(j) = u(j+1) - K(j+1, u(j+1))$$

where  $u(J) = T$ .

If we are willing to assume that  $X_p(1), X_p(2), X_p(3), \dots, X_p(Z_p)$  are independent and identically distributed and that

$$(12) g_p(n) = (1-a)a^n, \text{ for some } a \text{ independent of } p,$$

then an even simpler computation is possible. It is not claimed that these additional assumptions are realistic (the acoustic properties of real phones are much more complicated). However, they do produce reasonable results with a great savings in computation.

The extra assumptions allow us to ignore the durations of the phones by factoring out a factor which is the same for all sequences  $u[1:J]$ , namely the factor  $(1-a)^J a^T$ . Let's reformulate the Markov process, ignoring duration information. Let the state  $(j, t)$  correspond to the event  $U(j-1) \leq t < U(j)$  with  $U(j-1)$  otherwise unrestricted (time  $t$  occurs during phone  $P(j)$ ). Let  $\gamma_2(j, t)$  be

the probability for the best sequence leading up to the state  $(j,t)$  and producing the sequence  $y[1:t]$ . Then  $\gamma_2$  may be calculated by

$$(13) \gamma_2(j,t) = \text{Max}(\gamma_2(j-1,t-1), \gamma_2(j,t-1)) \text{PROB}(X_{p(t)}=y(t)).$$

Then the sequence  $u[1:J]$  may be calculated by

$$(14) u(k) = (\text{the greatest integer value of } t \text{ such that } t < u(j+1) \text{ and } \gamma_2(j-1,t-1) > \gamma_2(j,t-1)).$$

In machine-aided labeling it is only necessary to consider a single sequence  $p[1:J]$ . In a speech recognition problem, we wish to maximize not only over all possible sequences  $u[1:J]$  but also over all possible phonetic sequences  $p[1:J]$ , subject to the transition probabilities determined by the higher levels of the hierarchy. The computation of a function like  $\gamma_1$  or  $\gamma_2$  is not performed separately at the acoustic level, but is performed on a Markov process representing the integrated hierarchy.

### REPRESENTATION OF LEXICAL KNOWLEDGE AND PHONOLOGICAL RULES

This section discusses the computation of the conditional probability  $\text{PROB}(P[1:J]=p[1:J] | W[1:I]=w[1:I])$  where  $W[1:I]$  is the sequence of words in the utterance and  $P[1:J]$  is the sequence of phones. Each word is represented by an abstract network to which we may apply the re-estimation procedure of equations (21) and (22) of chapter II. The prototype word network consists of several columns of nodes (to simplify the discussion, assume that there are exactly two nodes per column) with each node connected to itself and to every node in its column and in the two following columns. Such a network is shown in Figure 1, where only the arcs leaving from one particular node have been shown.

If each node corresponds to a phone, then an arc which stays in the same column represents insertion of an extra segment. At this level we are primarily interested in representing insertions (and other phonological phenomena) made by the speaker, but as already mentioned there is always a choice between representing a given phenomenon at this level (where word-level context



## GENERAL WORD PROTOTYPE

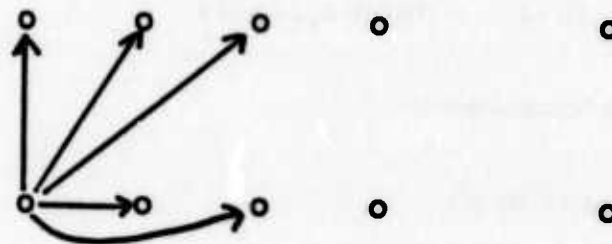


FIGURE 1

is known) or at the acoustic-phonetic level (where only one phone of context is known). An arc which skips a column represents a missed or deleted segment.

Let  $Y(t)$  be the phone which occurs at time  $t$ . Note that in this hierarchical system, the sequence which is the (unobserved) internal sequence at one level is the external sequence for the next higher level. Whether the acoustic level assumes a preprocessor or not, this next level assumes as its external sequence a sequence of phones (except there are several phenomena which could be represented at either level). Let  $X(t) = (X_1(t), X_2(t))$  be the internal state in our abstract word model, where

$$1 \leq X_1(t) \leq C, X_1(t) = \text{column number at time } t$$

$$1 \leq X_2(t) \leq R, X_2(t) = \text{row number at time } t$$

where  $C$  is the number of columns in the abstract model and  $R$  is the number of rows. For the purpose of this discussion, we take  $C$  fixed at the number of phonemes in the canonical version of the word (stored in a dictionary) and take  $R$  fixed at 2. Various values of  $C$  and  $R$  can be used and tested against the actual data.

This abstract network with the associated conditional probabilities represents the probability distribution of possible pronunciations of the word. We assume that the phonetic sequences corresponding to instances of the word are generated by a Markov process. Let

$$(15) \quad A((c_1, r_1), (c_2, r_2)) = \text{PROB}(X(t) = (c_2, r_2) \mid X(t-1) = (c_1, r_1))$$

$$(16) B(c,r,p) = \text{PROB}(Y(t)=p \mid X(t)=(c,r))$$

If we are given a collection of instances of a particular word  $W$ , and have estimates for  $A$  and  $B$ , we can use equations (21) and (22) to re-estimate  $A$  and  $B$  for the word  $W$ . Phonological rules which produce extra segments or deleted segments are represented by  $A$  and substitutions are represented by  $B$ . Phonological rules which apply across word boundaries can be represented by having several extra states at the beginning and end of each word and having the initial probability distribution depend on the context.

Several variations of this lexical model are also worth considering. If the acoustic level estimates not just the phones but the transeemes (pairs of phones as estimated by the acoustic transition between them, as in the ARCS and IBM-Watson systems) then the lexical level should have the distribution of  $Y(t)$  depend not just on  $X(t)$  but also on  $X(t-1)$ . It is possible to integrate the acoustic and lexical levels and directly re-estimate the representation of a word in terms of the acoustic parameters. This approach is being followed by Bakis. Another approach is to obtain a network representing the possible pronunciations of a word by applying a list of phonological rules written as production rules and applied to a baseform representation of the word. Automatic procedures for applying such a list of rules for the purpose of speech recognition systems have been developed by Cohen and Mercer[C1] and by Barnett[B5].

The explicit representation of phonological rules in the network is easily achieved at an expense of doubling or tripling the number of nodes in the network. However, it is not essential that an exhaustive set of phonological rules be used. In fact, the implementation of the **DRAGON** system described in Chapter IV has no explicit phonological rules and only one canonical pronunciation for each word. The reason that this representation is possible is that any phonological phenomena which are not introduced explicitly will be treated at the acoustic-phonetic level. Thus phonological substitutions can be mimicked by adjusting the probabilities in the  $B$  and  $E$  (equations (1), (2), and (3)) which represent the probabilities of substitutions and insertions and deletions at the acoustic level. The disadvantage of this approach is that the matrices represent less context than is available in the explicit representation of the phonological rules at the lexical level.

There is a serendipitous benefit in using the matrices  $B$  and  $E$  to represent acoustic-phonetic knowledge independently from the representation of the phonological rules. If the matrices  $B$  and  $E$  are estimated by running the acoustic preprocessor on a collection of training utterances, then any phonological rules which are left out in the prepared labeling of the training utterances are automatically absorbed into the estimates of  $B$  and  $E$ . Thus a perfect hand-labeled transcription of the training utterances is not only unnecessary, but undesirable. The best labeling for training purposes is an automatically generated labeling from a procedure knowing the sequence of words and having exactly the same lexical knowledge and phonological rules as the speech recognition system.

### REPRESENTATION OF SYNTACTIC AND SEMANTIC KNOWLEDGE

In building the integrated network, the lexical and phonological rule procedures take as input a network representation of the syntax and semantics in which each node of the network represents a word. It is clear that any regular (finite state) grammar can be represented by a finite network. In a speech recognition system the distinction between a regular grammar and an arbitrary context-free or context-dependent grammar is somewhat artificial. Consider the language generated by a particular grammar, not the sequence of words, but the sequence of acoustic events. It is not unreasonable to assume, for example, that the entries in the acoustic-phonetic matrix  $B(p,k)$  are all non-zero, although perhaps very small. Such a result would automatically be the case with pattern recognition based on *a posteriori* probabilities if the conditional probability distributions for the acoustic parameters are multi-variate normal distributions.

But if each entry in  $B(p,k)$  is non-zero, then at the acoustic level the language must include all possible sequences. Such a language can, of course, be represented by a finite network grammar. Thus the issue becomes not one of generating the proper language, but rather one of accurately modeling the conditional probabilities. The conditional probabilities may be context-dependent even for a language generated by a context-free grammar. The approach which has been used in the **DRAGON** system has been to enlarge the finite grammar to allow the conditional probabilities to be more accurately represented, but not to try to retain all of the context of the actual language.

The properties of probabilistic grammars have been studied by several investigators ([B10], [E1], [F3], [G2], [H1], [S1], [S2], [T4]). A probabilistic finite state grammar is a special case of a probabilistic function of a Markov process in which the entries in the matrix  $\{b_{i,j,k}\}$  of equation (5) of Chapter II are all zeros or ones (only the transitions are probabilistic). Thus such a grammar can be immediately represented in terms of our general model. However, there is still the problem of estimating the transition probabilities.

The general abstract model is not as well suited to representing semantic knowledge as it is to representing the other sources of knowledge which have been discussed. In the implementation described in Chapter IV, there has been no attempt to represent semantic knowledge. In fact, an argument could be made that, since there is no process corresponding to understanding the sentence, whatever knowledge is represented by the abstract stochastic model is of necessity not semantic knowledge. However, it should be noted that it is not necessary for the stochastic model to directly represent the semantic knowledge itself, but rather it is necessary for the model to represent the influence of the semantic knowledge on the probability distributions of possible sequences of words.

For example, it is possible to have a specialized task-specific module which is capable of understanding the utterances of a given task and which is capable of representing the set of utterances which are possible in a given context. The HEARSAY speech understanding system employs such a mechanism for the VOICE CHESS task. The task is to recognize chess moves that are spoken by a user who is playing a game of chess against the computer. The system has a separate module consisting of a chess playing program, TECH. Not only does the TECH program play chess with the user, but when it is the user's turn to move, TECH lists for the recognition system all moves which are possible in the given position and even rates the moves. Thus the TECH program provides semantic guidance for the recognition system. A similar mechanism may be used to obtain semantic knowledge for the DRAGON system. Once the list of legal moves is obtained and rated, this information may be used in setting the transition probabilities for the probabilistic grammar. The fine details may be lost, but much of the information will be represented, the quality of the representation depending on the complexity of the grammar.

There is even a mechanism by which the stochastic model can obtain some semantic information without a specialized module. Consider the goal of mimicking a human being who is trying to guess the next word in an utterance when given some limited amount of context. This person, who is capable of understanding the utterance, could use whatever semantic knowledge is available from the limited context. In this situation the semantic knowledge is more limited than that which is used by the TECH program, which knows the entire sequence of previous moves and hence the current board position, but it is still of value to the speech recognition system. The problem of obtaining the statistics for this type of semantic knowledge is part of the general problem of estimating the transition probabilities for a probabilistic grammar.

The transition probabilities for the grammar network can be estimated from statistics for a set of training sentences. A large set of training sentences should be used, but they only need to be transcribed orthographically, not phonetically, at this level of the hierarchy. If Bayesian statistics are used, the *a priori* probabilities could be set to achieve the same effect as a non-probabilistic use of the grammar. The *a posteriori* probabilities would then be a strict improvement (as judged by performance on the training sentences).

To the extent to which the statistics of the training sentences reflect the true probabilities for spontaneous utterances for the specific task, the probability network represents not only the syntax of the task but also all of the predictive information which can be obtained from the semantics of the available context. That is, if the true probabilities were known, the probability network would be an optimal predictor for a given amount of context, and therefore would predict at least as well as a human who is given the same amount of context and who presumably is capable of understanding the sentence (although the context in this case is not necessarily the whole sentence).

Inter-sentence semantics can also be introduced into the probability network. One way to use inter-sentence semantics is to employ a user model. Suppose there is a model for the user in a particular task such that the model gives probabilities for the user transitioning among a finite number of states depending on the types of utterances which the user has made. Conceptually this model fits in easily as an extra level of the Markov hierarchy. Computationally it requires that

conditional probabilities be estimated separately for each user state. A user model is especially valuable if certain key sentences trigger user transitions with probability one and if for each user state only a small subset of the general grammar is used. Then there is a savings in both the computation and the storage requirements.

### SUMMARY

Each of the major sources of knowledge in a speech recognition system can be represented as a stochastic process (usually in more than one way). In speech recognition each knowledge source involves an idealized process  $X(1), X(2), X(3), \dots, X(T)$  which is not observed and a process  $Y(1), Y(2), Y(3), \dots, Y(T)$  depending on the  $X$  process. The  $Y$  process is either directly observed or is inferred from lower level knowledge sources in the speech recognition system. Such a dual process can be modeled as a probabilistic function of a Markov process. In the **DRAGON** system such a model is used for each of the knowledge sources.

The speech recognition knowledge sources fit into a hierarchy such that the integrated system also is a probabilistic function of a Markov process. Such a simple general model for speech recognition permits a recognition program which is just a simple implementation of general network search algorithms. Such an implementation of the **DRAGON** system is described in Chapter IV.



## INTRODUCTION

In Chapter II, the general properties of a probabilistic function of a Markov process were discussed. Chapter III explained some of the ways in which the knowledge sources of a continuous speech recognition system can be represented by such a model. This chapter describes an implementation of a complete speech recognition system based on these models. This implementation is intended as a preliminary system demonstrating the practicality of building a complete system based entirely on the abstract Markov model. It is not intended as a final system demonstrating the full power of the techniques described here. Each knowledge source is given a simplified representation, and the probabilities in the networks are estimated *a priori* rather than by any automatic re-estimation procedure.

The system is simple, but it is a complete speech recognition system. Starting with knowledge represented in conventional forms—a context-free grammar, a phonetic dictionary, an arbitrary set of acoustic parameters—there is a set of programs for constructing the integrated Markov model, and a general recognition program which can recognize speech for any task based on the integrated network which has been constructed by the other programs. There is some training which is dependent on the talker and on the set of acoustic parameters, but which is independent of the task. This training is done by selecting by hand a set of prototypes for the acoustic segments from a set of utterances by the talker for whom the system is to be trained.

This implementation of the **DRAGON** system consists of five programs: **MAKDIC**, **MAKGRM**, **MAKNET**, **GETPRB**, and **DRAGON**. For each program, a brief description will be given of what it does and of how it does it. The system has been tested on a set of 102 utterances with about 20 utterances from each of 5 interactive computer tasks. The 5 tasks are **VOICE CHESS** (the user speaks his moves while playing chess against the computer), **DOCTOR** (the user asks medical questions and the computer simulates a patient), **DESK CALCULATOR** (the computer acts as a desk calculator for spoken commands), **NEWS** (the computer gives the current news stories whose subjects match a spoken specification), and **FORMANT** (the computer generates various kinds of graphic displays of speech data, according to spoken requests). The grammars for these 5 tasks are given in Appendix B, some sample utterances in Appendix E.

## MAKDIC

MAKDIC reads a phonetic dictionary and writes a file describing a network representation for each word in the dictionary. It is this program which would contain any knowledge of within-word phonological rules. Actually, the current implementation of **DRAGON** does not use any explicit phonological rules, so the output of MAKDIC is just a one-to-one translation of the phonetic dictionary. Each word is represented by a linear network with each node connected to itself and to the following node.

A phonetic dictionary including all the words for the 5 tasks is given in Appendix A. The dictionary is written at a very broad phonetic level and has been edited by hand to break up diphthongs and stops into acoustic segments. Certain groups of phones which were distinct in the original dictionary were replaced by a single symbol for each group. This grouping was performed when the phones within a group were practically indistinguishable under the acoustic parameterization used in this implementation. The hand editing was designed to achieve an effect like the lexical model of equations (III.15) and (III.16) of Chapter III, with  $C=1$ .

The list of acoustic segment types which appear in the dictionary is given in Table 1. A section of the dictionary is shown in Table 2. The complete dictionary is Appendix A. A flow-chart of the MAKDIC program is shown in Figure 3, and a section of its output file is shown in Table 4. In this implementation, since no phonological rules are applied, the MAKDIC program just goes through the dictionary word-by-word and goes through each word phone-by-phone.

The section of output shown in Table 4 is interpreted as follows: 251 is the index of the word "with" in the dictionary. 4 is the number of phonetic segments in the word. For each of the 4 phonetic segments there are two lines. The first 1 in line 2 is the index of the current phonetic segment within the word. 0 is the internal code for this segment type, "-". The next 1 indicates the number of arcs leading to this node from nodes other than itself. 0 is the probability of this node being skipped. 900 indicates that the probability of the arc from this node to itself is .900. (All probabilities are multiplied by 1000 and truncated to integers.) Next follows a list of all the nodes (other than the node itself) with arcs leading to the current node (in each case there is only one). The 0 in line 3 is the index within the word of the node which has an arc leading to the

## ACOUSTIC SEGMENT LABELS

-	silence, pause, voice-bar
AX	(A)BOUT
B	A(B)OUT (release-aspiration portion)
AH	N(U)MBNESS
T	(T)ELL (release-aspiration portion)
AE	H(A)MMING
S	(S)EVEN, (Z)ERO
L	(L)ET
UW	D(O)
F	(F)EVER, WI(TH)
ER	(R)OOK, FEV(ER)
EH	L(E)T
IH	K(I)NG
D	(D)IVIDE (release-aspiration portion)
P	(P)AWN (release-aspiration portion)
N	(N)INE
AO	P(AW)N
AA	(O)CTAL
M	(M)UMPS
SH	BI(SH)OP, MEA(S)URE
K	(K)ING (release-aspiration portion)
IY	QU(EE)N
NX	KI(NG)
G	(G)IVE (release-aspiration portion)
Y	(Y)OU
V	FI(V)E
W	(W)E
OW	ZER(O)
WH	(QU)EEN (release-aspiration and devoiced semi-vowel)
HH	(H)AMMING
UH	R(OO)K

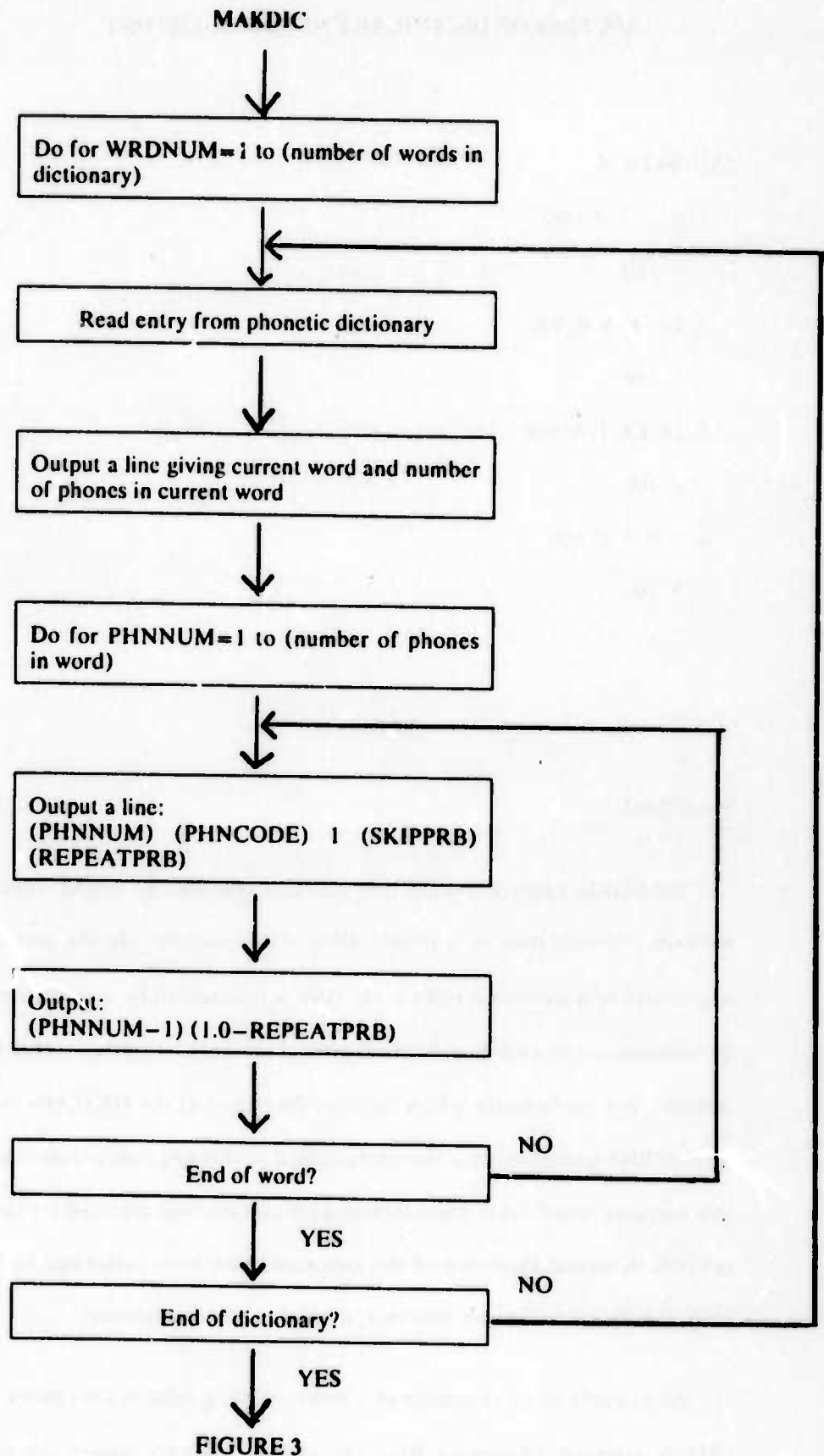
TABLE I

## SECTION OF DICTIONARY

WITH	- W IH F
USING	- Y UW S IH NX
HAMMING	- IH AE M IH NX
HANNING	- HH AE N IH NX
BLACKWELL	- B L AE - K W EH L
RECTANGULAR	- ER EH - K - TEH IH N - G Y UW L AA ER
TRIANGULAR	- TER AA IH EH IH N - G Y UW L AA ER
FREQUENCY	- F ER IY - K W EH N - S IY
BANDWIDTH	- B AE N - D W IH - D F
CENTER	- S EH N - TER
CUTOFF	- K AH - TAO F
LOW	- LOW
PASS	- P AE S
HIGH	- HH AA IH

TABLE 2

current node. The 100 indicates that the probability of following this arc is .100. The remaining



phonetic segments are represented similarly.

## SECTION OF DICTIONARY NETWORK LISTING

251 WITH 4

1 0 - 1 0 900

0 100

2 16 W 1 0 900

1 100

3 28 IH 1 0 900

2 100

4 7 F 1 0 900

3 100

TABLE 4

## MAKGRM

MAKGRM reads a context-free grammar specified by a BNF representation and writes a network representation of a related finite-state grammar. In the current implementation each appearance of a terminal symbol in the BNF is represented by a separate node in the network, but all appearances of each non-terminal symbol are linked together. This linking implies a loss of context. For the tasks for which this implementation of the **DRAGON** system has been used, the original BNF grammars have been hand edited so that any non-terminal symbol which appeared in two contexts which were important to keep distinct was replaced by two distinct non-terminal symbols. A limited expansion of this type could have been performed by the MAKGRM program itself, but since it was a one-time task, it was done by hand instead.

An example of an expansion of a non-terminal symbol is the symbol <piece> in the VOICE CHESS grammar (Appendix B). The symbol <piece> names the piece taking the action, <pieceh> is part of the location for that piece, <piecec> is a piece being captured, and <pieced>

is either part of the location to which a piece is moving or part of the location on which a piece is being captured.

Note that if either the left contexts or the right contexts are identical for two uses of the same non-terminal, then the uses do not need to be distinguished. If the left contexts are identical, then there is no context information to be remembered. If the right contexts are identical, then the left context information does not influence the interpretation of the rest of the sentence. Note that `<pieced>` has two different uses in the CHESS grammar, with different left contexts, but identical right contexts.

The current version of MAKGRM performs a straight-forward translation of the BNF. Each production is represented by a simple linear network. All the productions with a particular left hand side are linked together with a dummy node at each end. These dummy nodes are then linked to any nodes in the grammar which represent uses of the non-terminal symbol that is the left hand side of these productions. A part of the FORMANT grammar is shown in Figure 5. Figure 6 shows the network in which each production has been represented by a simple linear network. Figure 7 shows the network after the initial and final nodes for each non-terminal symbol have been linked to the uses of that non-terminal. A flowchart for MAKGRM is given in Figure 8.

**BNF GRAMMAR**

```

<phr>::=      <spec>
               <phr><spec>

<spec>::=      A <wind> WINDOW OF <num> POINTS
               <num> COEFFICIENTS
               FILE NUMBER <num>
               UTTERANCE NUMBER <num>
  
```

FIGURE 5



## PARTIALLY CONNECTED NETWORK

 $\langle \text{phr} \rangle ::=$  $\langle \text{spec} \rangle$  $\langle \text{phr} \rangle \longrightarrow \langle \text{spec} \rangle$  $\langle \text{spec} \rangle ::=$ A  $\longrightarrow$   $\langle \text{wind} \rangle \longrightarrow$  WINDOW  $\longrightarrow$  OF  $\longrightarrow$   $\langle \text{num} \rangle \longrightarrow$  POINTS $\langle \text{num} \rangle \longrightarrow$  COEFFICIENTSFILE  $\longrightarrow$  NUMBER  $\longrightarrow$   $\langle \text{num} \rangle$ UTTERANCE  $\longrightarrow$  NUMBER  $\longrightarrow$   $\langle \text{num} \rangle$ 

FIGURE 6

## SECTION OF GRAMMAR NETWORK

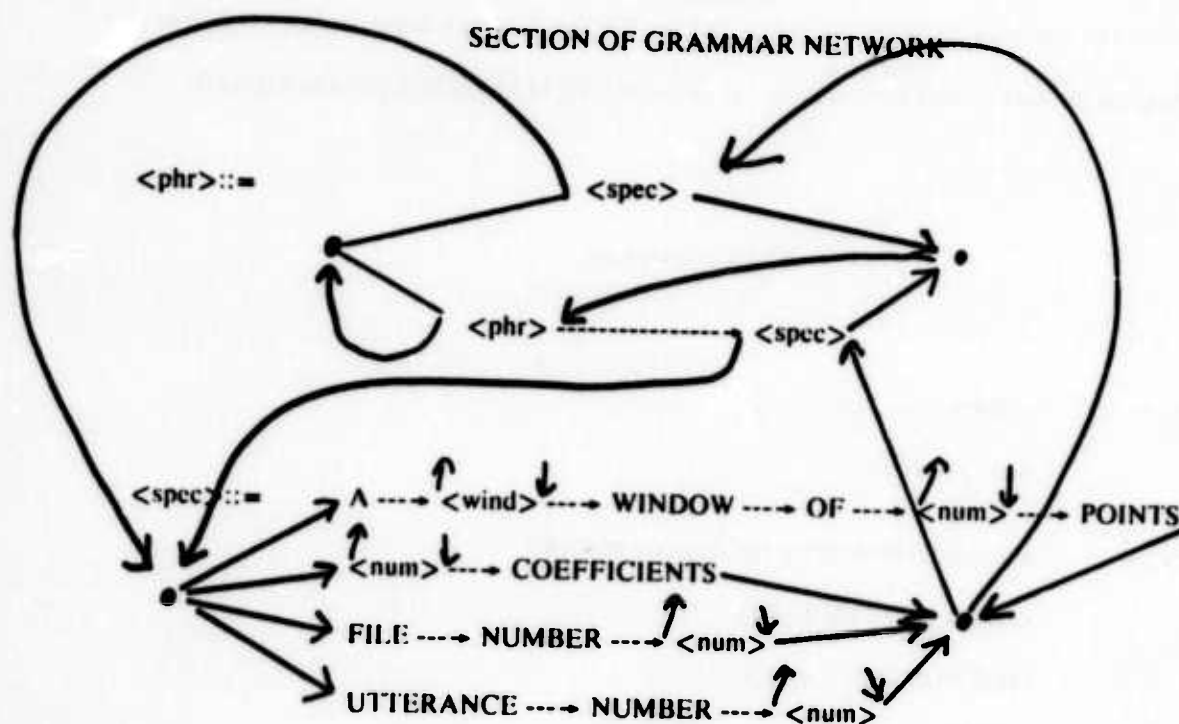


FIGURE 7

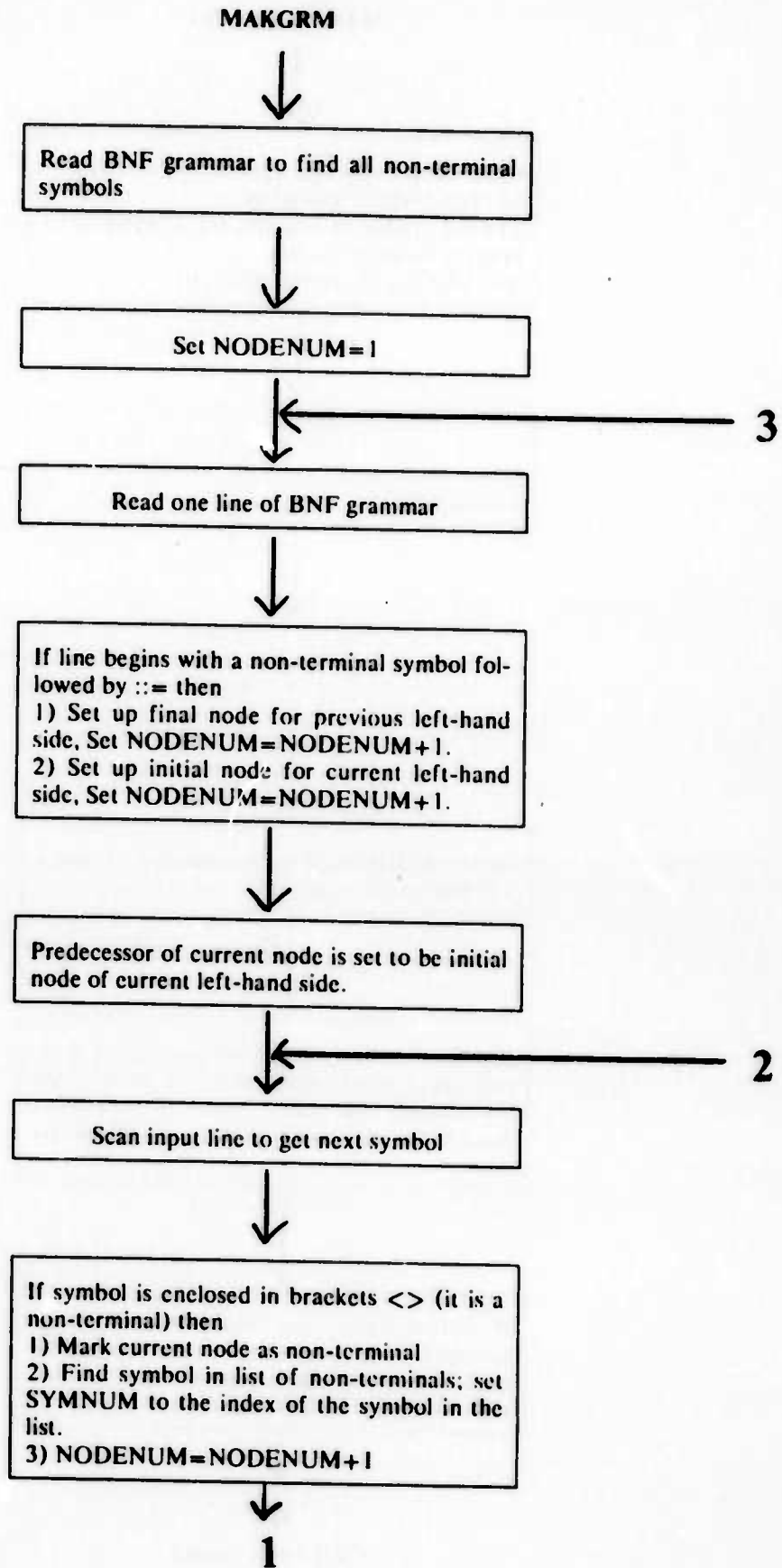


FIGURE 8

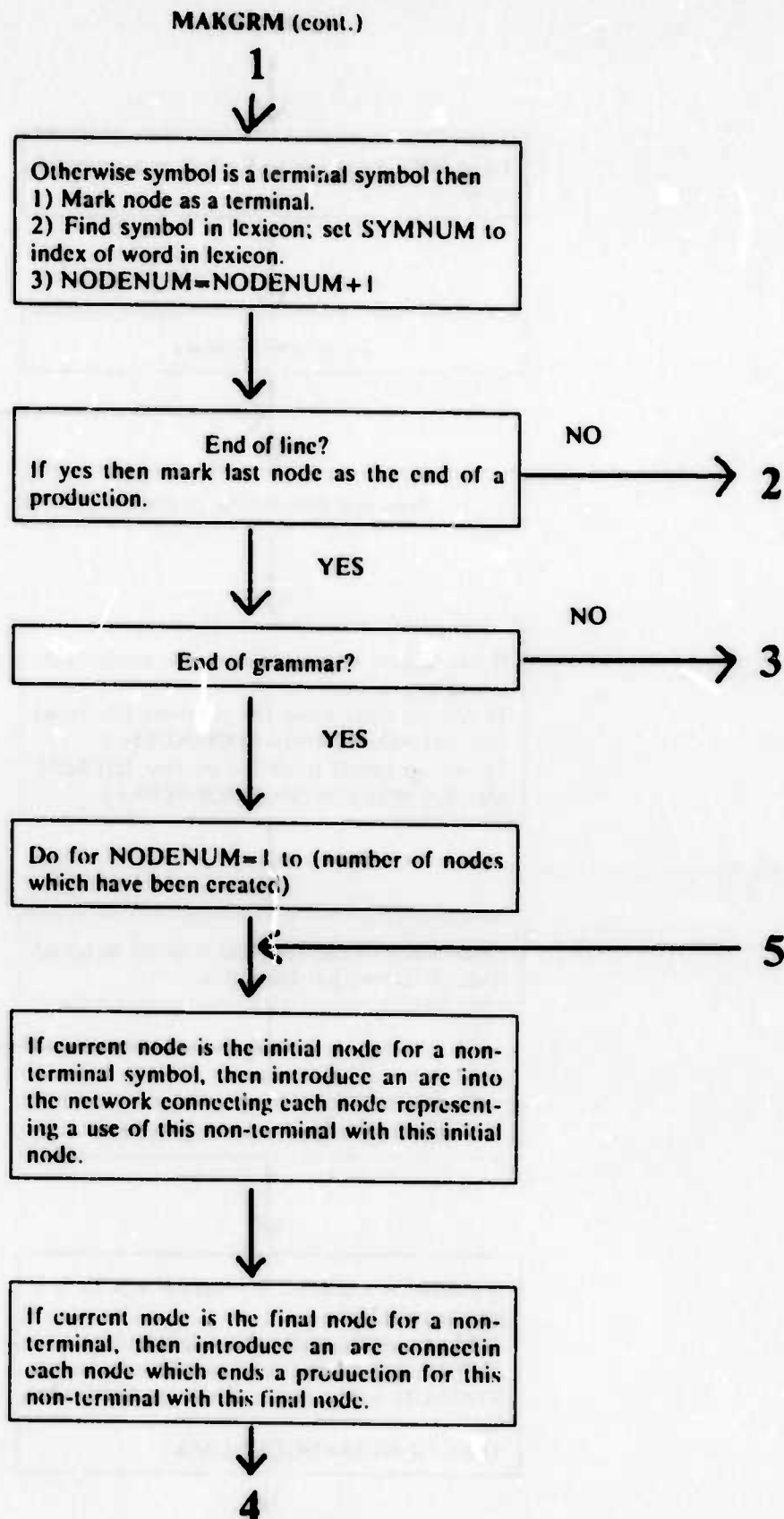
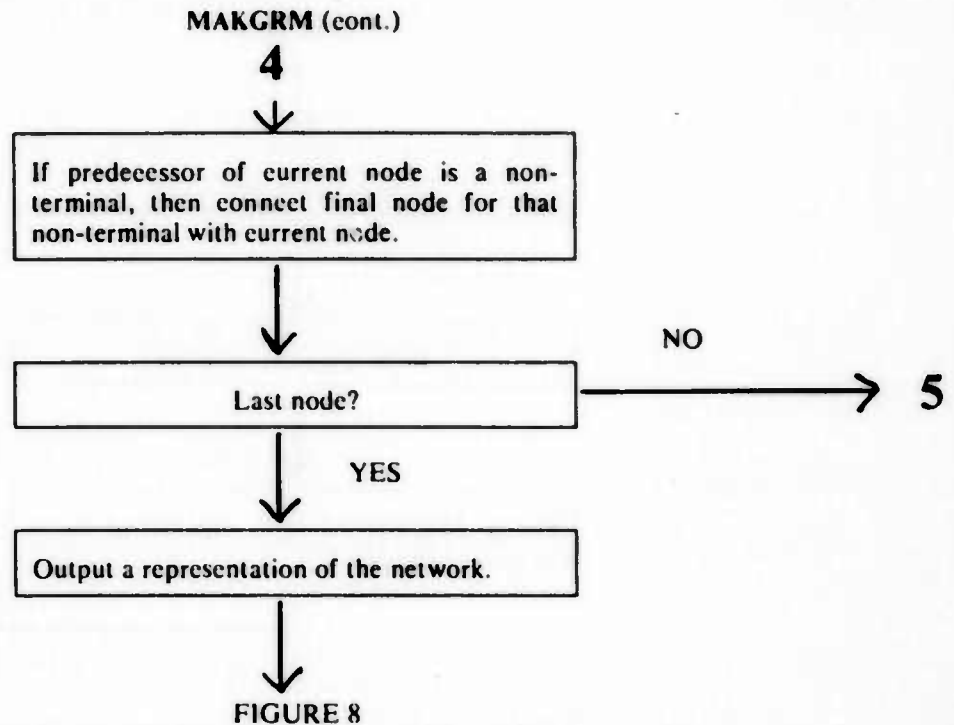


FIGURE 8 (cont.)



### MAKNET

MAKNET takes as input a network representation of a grammar (produced by MAKGRM) and a network representation of the dictionary (produced by MAKDIC). It produces an integrated network by substituting the appropriate word network for each node in the grammar network. Phonological rules which apply across word boundaries could be used to adjust the network after the substitution.

MAKDIC, MAKGRM, and MAKNET must keep track of the transition probability associated with each arc of the network. At present simple default values are used. MAKDIC assigns a probability of .9 to any arc leading from a node back to itself, and .1 for any arc leading to the next node. This corresponds to acoustic parameters sampled once every 10 milliseconds, with no presegmentation, and an average phone duration of 100 milliseconds, based on the acoustic-phonetic model of equations (III.12), (III.13), and (III.14).

The complete input and output for MAKGRM and MAKNET is shown for a simple language in Appendix C. First the simple BNF grammar is given. Next the output file of MAKGRM is shown. Consider the productions with the non-terminal symbol <request> as the left-hand side.

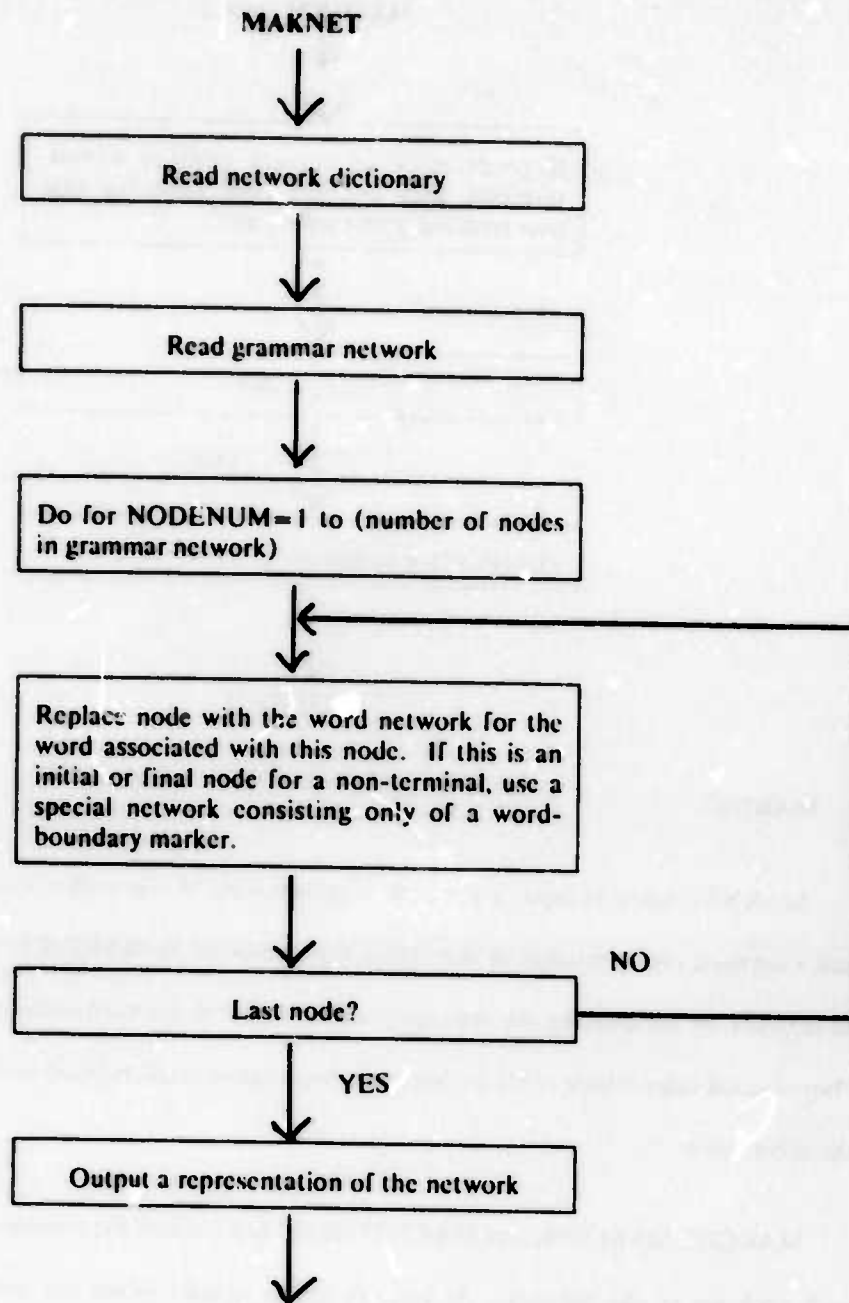


FIGURE 9

The sub-network for these productions begins with the line "<request>::= 6 -2 1." The 6 is the node number for this node, which is the special initial node for this left-hand side. -2 indicates that this node is associated with the second non-terminal symbol. 1 indicates that this node has only 1 arc leading to it. (In this implementation, each arc is listed with the node to which the arc points and transition probabilities are given conditional on the state after the transition, rather than in the conventional form presented in Chapter II. This form has been chosen for the convenience of the implementation, the two theoretical models are equivalent.) 2 (on the next line)

is the node number of the node with an arc leading to the current node, and 1000 indicates that the probability of following this arc is 1.000.

"Compute" is the word associated with the next node, which is node 7. It is a terminal symbol and 291 is its index in the dictionary. This node has 1 predecessor, which is node 6 (with probability 1.000). Node 8 is associated with the third (-3) non-terminal symbol <func-phr>. The node has 1 predecessor, node 7. Node 9 is associated with the word "Use" which has index 222. The node has 1 predecessor, node 6 (which is the initial node for this set of productions). Node 10 is associated with the non-terminal symbol <param-phr>, and its only predecessor is node 9. Node 11 is the final node for this set of productions (with <request> as the left-hand side). It has two predecessors, node 17 and node 32, which are equally likely. Node 17 is the final node for the productions for the symbol <func-phr>, which is associated with node 8. Node 32 is the final node of the productions for the symbol <param-phr>.

MAKGRM assigns an equal probability to all arcs leading to the same node. This default condition implies that the **DRAGON** system is currently using no semantic knowledge, not even statistically (except for any semantic knowledge which is included in the grammar itself).

The output of MAKNET is a combination of the outputs of MAKDIC and MAKGRM. Each node corresponds to an acoustic segment. Except at word boundaries, each node has only one predecessor besides itself. Notice that there are many nodes marked "-". These silence nodes are common because the dictionary indicates that every word begins with a silence (because the word may be preceded by a pause). The dynamic time warping is sufficiently powerful that these silences can be allowed throughout the network. If no silence is actually present in the acoustic signal, then the dynamic time warping will shrink the duration of time assigned to the "-" node to a single 10 millisecond segment.

#### GETPRB

GETPRB takes as input a set of acoustic parameter values and produces as output a vector of probability estimates. Each entry in the probability vector represents the conditional probability



of producing the given set of acoustic parameter values, conditional on the actual phone at the time of the acoustic observation being the phone corresponding to that particular position in the probability vector.

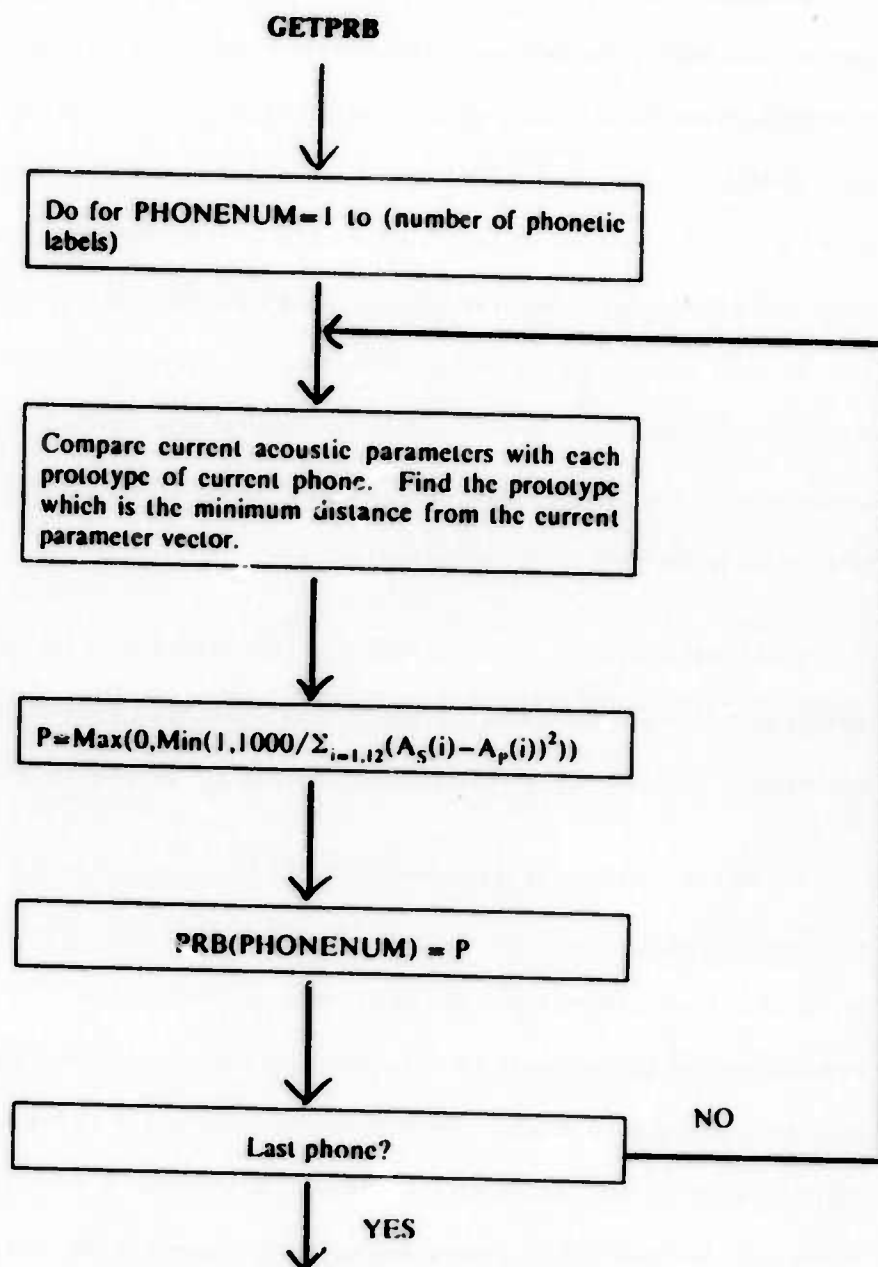


FIGURE 10

Any convenient set of acoustic parameters and any matching procedure could be used here. The current version of the DRAGON system uses 12 acoustic parameters sampled once every 10 milliseconds. The basic parameters are an amplitude measure and a zero-crossing-count for each of five filter bands, and for the unfiltered signal. The five filter bands are

A1, Z1: 200-400 Hertz

A2, Z2: 400-800 Hertz

A3, Z3: 800-1600 Hertz

A4, Z4: 1600-3200 Hertz

A5, Z5: 3200-6400 Hertz

AU, ZU are for the unfiltered signal.

The vector of twelve parameters is normalized in a non-linear fashion by dividing A1, Z1, A2, Z2, A3, Z3, A4, Z4, A5, Z5 each by the sum of the twelve parameters and multiplying by 1000. No attempt has been made to find an optimal non-linear transformation; this transformation has been selected by informal experimentation with a small number of alternative transformations. The reason a transformation is introduced is that so many of the consonants are so low in amplitude in all the bands that they are difficult to separate by any simple metric. The measurements on the unfiltered signal, AU and ZU, are not normalized, so they retain the information of overall amplitude.

The amplitude measures and zero-crossing counts are normalized together because, especially for the low amplitude cases that we are trying to separate, the zero crossing counts also give a kind of amplitude measure. This phenomenon occurs because the zero crossing counter only counts cycles which exceed a certain threshold. Thus for signals whose amplitude is near the threshold, the zero crossing count is actually a sensitive measure of the amplitude. For strong signals the zero crossing count measures the frequency of the major spectral peak within a particular band.

GETPRB measures the distance between a particular vector of (normalized) acoustic parameter values and a particular prototype by a simple Euclidean distance. However, there are several prototypes for each phone. The prototypes were selected by hand from a set of 50 training sentences spoken by the same talker as the one on whom the system has been tested.

One prototype for each phone was found among the 50 sentences by hand. Each prototype was just the (normalized) vector of acoustic parameter values for some 10 millisecond segment occurring during an instance of the desired phone. Using the GETPRB from these initial proto-

types, **DRAGON** was run as a machine-aided labeling program on the same 50 sentences (that is, **DRAGON** was told the sequence of words in each sentence, but not the times at which they occurred).

The output of the machine-aided labeling was then carefully checked by hand (there were about one or two corrections per sentence). The labels produced by GETPRB were then compared with this hand-checked segmentation. Whenever there was a steady-state acoustic segment for which no prototype had probability greater than .1, a new prototype was added for the phone which the hand segmentation marked as occurring at that time.

An arbitrary transformation is applied to convert the Euclidean distance measure to an estimate of the conditional probability. The transformation is given by equation (1).

$$(1) \quad P = \text{Max}(0, \text{Min}(1, (1000 / (\sum_{i=1,12} (A_S(i) - A_P(i))^2))))),$$

where  $A_S(i)$  is the value of the  $i$ th acoustic parameter for the current sample, and  $A_P(i)$  is the value of the  $i$ th acoustic parameter in the prototype.

A sample of the acoustic labeling produced by GETPRB is given in Appendix D for a portion of the utterance "Use a Hamming window of five hundred twelve points." First a table of the values of the 12 (normalized) acoustic parameters is given; then a table of the top 7 prototypes for each 10 millisecond segment is given. Each row in each table represents one 10 millisecond segment. The segment number is in the first column. In the parameter table the remaining columns are the values of Z1, A1, Z2, A2, Z3, A3, Z4, A4, Z5, A5, ZU, and AU, respectively.

In the table of labels, each label is followed by a number which is its index in the list of prototypes. Frequently several prototypes for the same label occur among the top 7 prototypes. The final two columns are the squares of the Euclidean distances from the current set of acoustic parameter values to the best and second best prototypes.

From time 95 to time 108, the parameters are almost all 0, and "-" is the best prototype. Then "Y" is the best label from 109 to 111. "UW" is best, or one of the best, from 113 to 134. Occasionally another label (IY, AX, L) is rated best, but none of these labels scores high through-

out the time from 113 to 134. This section of time would reliably be marked as "UW," from the acoustic information alone. The section from 136 to 138 is a transition between the "UW" and the "S," and no label scores well. From 139 to 144 is the "S." Notice that parameters A4 and Z4 are 0 throughout this segment. This is a feature for distinguishing "S" from "SH," and the system reliably labels "S" and "SH" with these acoustic parameters.

There is no real acoustic evidence for the word "a," and the vowels and nasals of the word "Hamming" are not very clear. At this point the value of an integrated system with other sources of knowledge becomes clear. Rather than doing segmentation and labeling from the acoustics alone, the system makes all decisions in terms of the integrated network representation. The system was able to select, using the labels shown here, the word "Hamming" over all alternatives, including the word "Hanning." However, the system missed the word "twelve" later in the utterance.

## DRAGON

The main recognition program, DRAGON, is just an implementation of equations (18), (19), and (20) of Chapter II. The B matrix is provided in implicit form by the procedure GETPRB. The A matrix is represented by the network produced by MAKNET and the default transition probabilities. In comparison with a general transition matrix, the matrix is very sparse (almost all of its entries are zero). The network corresponds to a compacted representation of the transition matrix. Each node in the network corresponds to a row of the matrix, and each non-zero entry in that row corresponds to an arc in the network leaving that node. Since there are usually only two non-zero entries per row, the representation is very compact. Thus the 2356x2356 element transition matrix for the formant tracking task is stored in a few thousand memory locations.

Equation (20) of Chapter II requires that a back pointer be saved telling the best way to get to each node at each point in time. Again it is possible to make use of the extreme sparseness of the A matrix. Since a list is kept of all arcs leading to a given node, a compact back pointer can be kept using only enough bits to select one of the short list of arcs. These back pointers are stored as variable length bytes, fitting as many pointers per memory location as possible. This packed representation of the back pointers makes it possible for the current version of DRAGON to keep

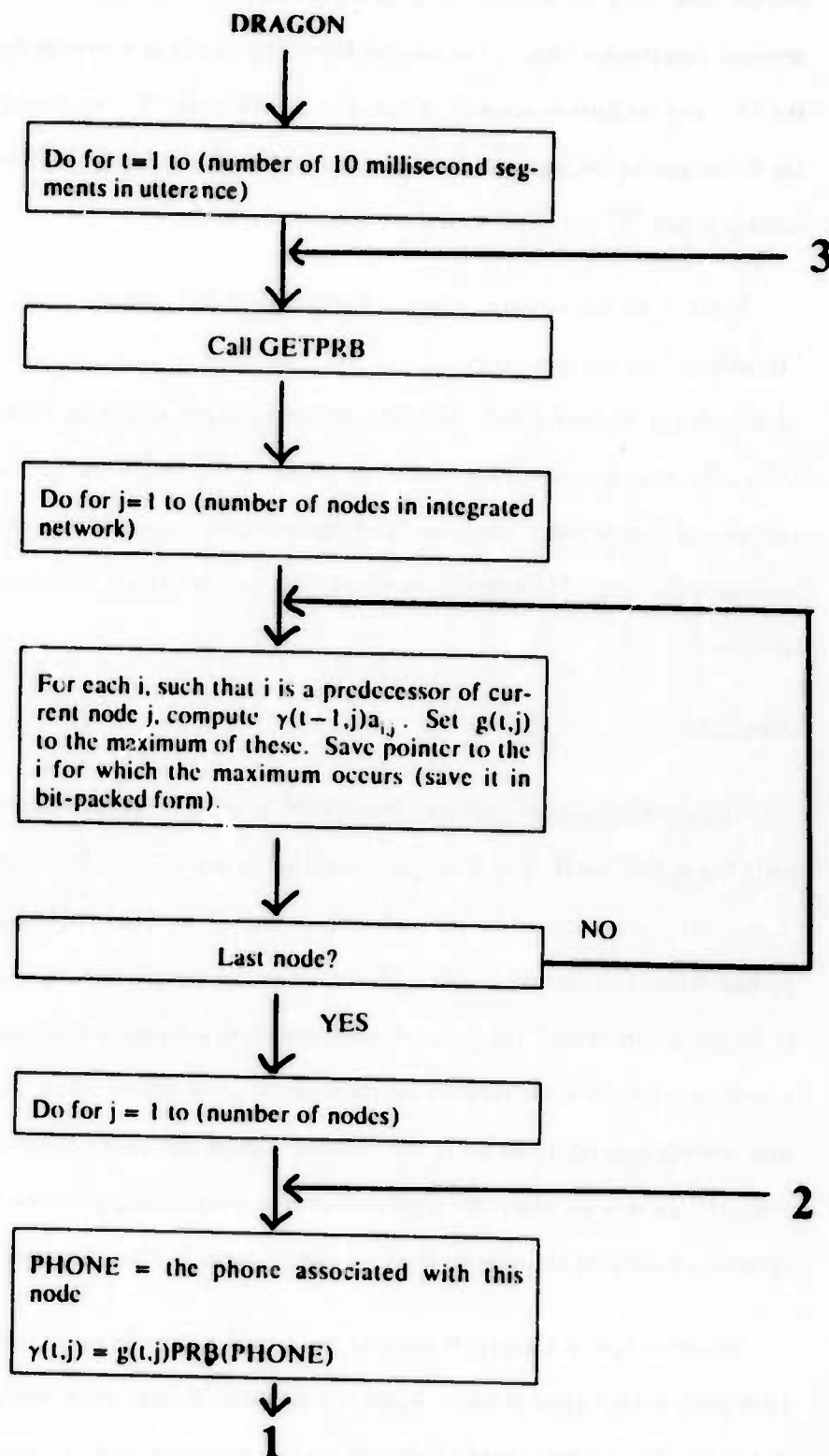
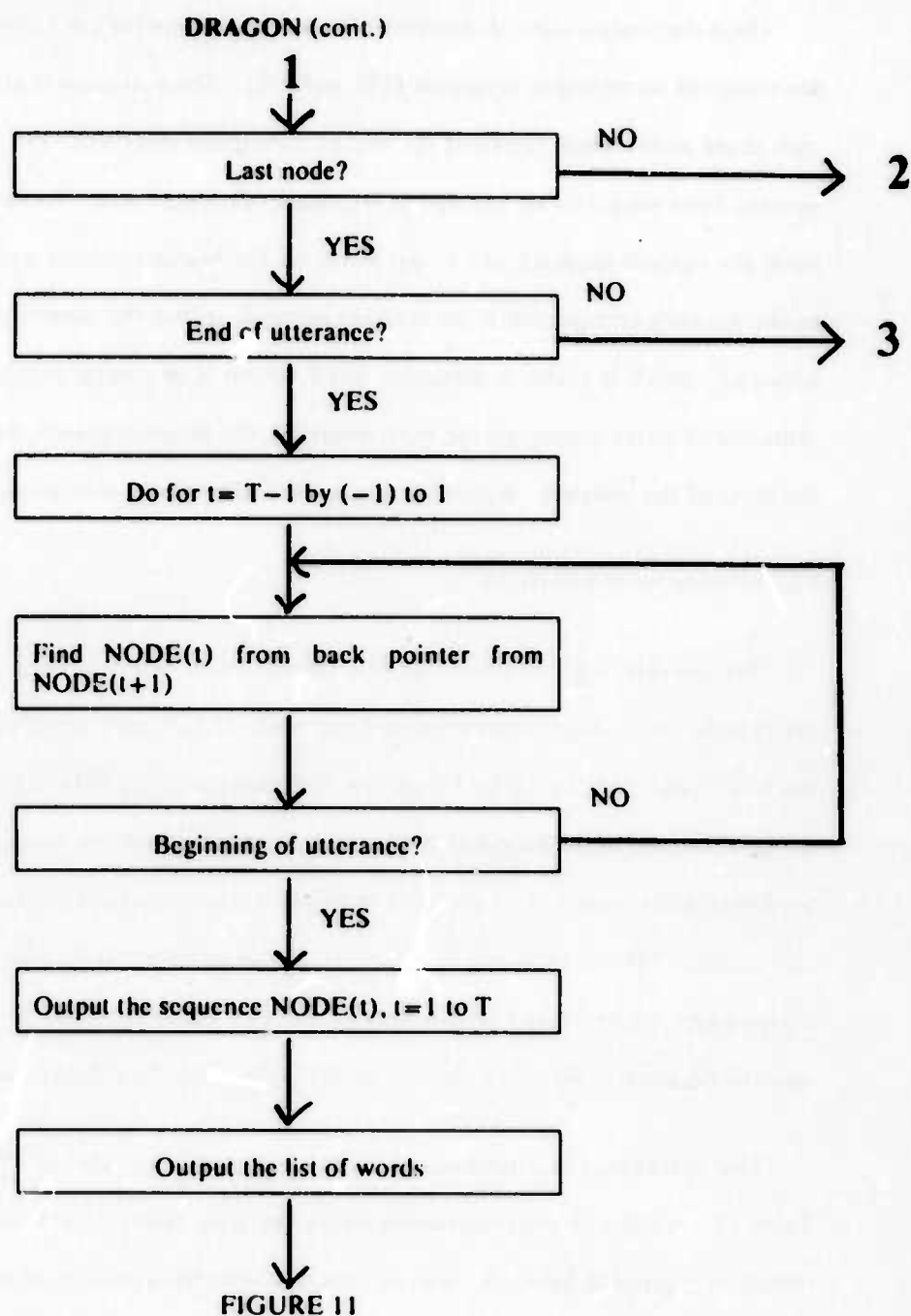


FIGURE 11

all the back pointers for a six second utterance in core memory. In fact, the back pointers for a given 10 millisecond segment for the formant tracking task fit in 73 memory locations (36 bits each).



A flowchart of the DRAGON program is shown in Figure 11. The program performs the computation of equation (18) for  $t = 1, T$ . Each node  $j$  is considered in turn. Since in this implementation the implicit  $b_{i,j,k}$  is independent of  $i$ , the value of  $i$  for which the maximum occurs in equation (18) depends only on  $\gamma(t-1, i)$  and  $a_{i,j}$ . This value is found and saved as a back pointer. If  $p$  is the phone corresponding to node  $j$ , then the  $b_{i,j,k}$  for the current acoustic parameter values is the number which GETPRB returns in position  $p$  of the probability vector. The computation of  $\gamma(t, j)$  is completed by multiplying by this factor.



Once the computation of equation (18) has been done for  $t = 1$  through  $T$ , the back pointers are retrieved according to equations (19) and (20). The maximum in equation (19) is taken only over those nodes which represent the end of a complete utterance. For the grammars which have actually been used, this set has always consisted of a single node. As the back pointers are traced back, the optimal sequence of internal states for the Markov process is obtained. Since each node in the network corresponds to an acoustic segment within the acoustic realization of a particular phoneme, which is within a particular word, which is in a particular place in the grammar, the sequence of states determines the word sequence, the phone sequence, the segmentation times, and the parse of the sentence. Whichever sequence is of interest can be printed out.

### PERFORMANCE RESULTS

The current implementation of the **DRAGON** system has been tested on a total of 102 utterances, with about 20 utterances from each of five interactive computer tasks (described briefly on page 34). In Tables 12-14, the performance of the **DRAGON** system is compared with the performance of the **HEARSAY** speech understanding system. Because this implementation of the **DRAGON** system has no semantic component, the semantic module of the **HEARSAY** system was disabled for this experiment. These results were obtained by Lowerre[L3] in a study of the comparative strengths and weaknesses of the two systems. Both of the systems used the 12 acoustic parameters described above, sampled once every 10 milliseconds.

The percentage of utterances correctly recognized in each task by each system is given in Table 12. All 102 of these utterances are by the same talker. The percentage of words correctly identified is given in Table 13. The amount of computation time required by the current system is given in Table 14. These times are the amount of central processor time on a PDP-10 computer as a multiple of the length of the utterance.

Overall the **DRAGON** system recognized 49% of the 102 utterances and identified 83% of the 578 words. An utterance is counted as being correctly recognized if all of the words in the utterance are correctly analyzed. Because of factors such as varying sentence length, the percentage of words correctly identified is more stable for different tasks than the percentage of utterances recognized. Notice that the **DRAGON** system maintained a level of 84% of the words correctly

## ACCURACY OF UTTERANCES RECOGNIZED

Task	size of lexicon	no. of utts	Hearsay % correct	Dragon % correct	Hearsay % missed	Dragon % missed
Chess	24	22	32	68	9	0
Doctor	66	21	24	76	33	0
DesCal	37	23	22	17	13	8
News	28	18	50	50	11	0
Formant	194	18	33	33	44	5
		102	31	49	21	3

The % correct figure is the percent of the total utterances that were correctly recognized. The % missed figure is the percent of the total utterances that were completely missed, i.e. no words were correctly identified.

TABLE 12

## ACCURACY OF WORDS IDENTIFIED

Task	size of lexicon	no. of words	Hearsay % correct	Dragon % correct
Chess	24	130	69	94
Doctor	66	92	49	88
DesCal	37	116	53	63
News	28	98	74	84
Formant	194	142	33	84
		578	55	83

TABLE 13

identified on the interactive formant tracking task.

The FORMANT task is considerably more complex than the other tasks. It has a vocabulary of 194 words and an infinite language with approximately  $16^n$  sentences of length  $n$  words. Each of the other tasks has a finite language with the number of possible sentences ranging up to several hundred million. The HEARSAY system was able to recognize 33% of the utterances for this task, but it only identified 33% of the 142 words. It missed 44% of the utterances completely, and the standard deviation of its computation time is higher than for the other tasks.

This implementation of the DRAGON system was developed using training sentences (by the

## TIME NEEDED FOR RECOGNITION

Task	Hearsay			Dragon			Size of Dragon network
	ave. times real time	Std. Dev.	SD/ave	ave. times real time	Std. Dev.	SD/ave	
Chess	13.7	2.6	.19	48.0	.6	.013	410
Doctor	9.4	3.8	.40	67.4	1.1	.016	702
DesCal	15.5	9.4	.61	83.1	1.0	.012	916
News	10.8	6.4	.59	54.7	.6	.011	498
Formant	44.4	23.5	.53	173.8	3.3	.019	2356

For the **DRAGON** system:

$$(\text{recognition time}) = (\text{utt length})(20.9 + .067(\text{net size}))$$

This is accurate to within about 3%.

TABLE 14

same talker) from the tasks **CHESS**, **DOCTOR**, and **FORMANT**. The **HEARSAY** system was developed for tasks **CHESS**, **DOCTOR**, **DESCAL**, and **NEWS**. In no instance were any of the utterances used in training the systems included in the test results reported here. One reason the performance of the **DRAGON** system on the **DESCAL** task was inferior to its performance on the other tasks is that the **DESCAL** task includes several words which are syntactically equivalent and which are phonetically similar under the analysis used by the current system. No attempt has been made to provide extra phonetic prototypes for this task.

The small standard deviation in processing time for different utterances within a task is a feature of the optimal search algorithm used in the **DRAGON** system. A complete search is done for the globally optimum path through the network. The Markov model allows this global optimum to be found in a time which is proportional to the length of the utterance. If the words are clear and easily recognized, the complete search takes just as long as when the words are unclear and difficult to recognize. On the other hand, the system never takes longer than this fixed time, and it always finds some path through the network. In Table 15, results are given for an earlier version of the **DRAGON** system for each of the 18 utterances in the **FORMANT** task. The

property which should be noticed in these figures is that the processing time does not depend on how many errors are made in analyzing an utterance.

### ACCURACY AND TIME FOR INDIVIDUAL UTTERANCES

#### Task: Interactive Formant Tracking

Phrase#	#In	#Out	#Cor	#SemCor	Length	Main	Aco
1	6	6	6	6	2170	126.9	18.7
2	9	8	8	8	4270	119.4	18.7
3	8	8	8	8	3730	119.4	18.3
4	9	8	7	7	3690	118.5	18.6
5	7	7	5	5	3490	123.7	18.6
6	9	9	9	9	5670	115.9	18.5
7	10	10	10	10	4510	121.2	18.4
8	7	7	7	7	3200	124.5	18.3
9	11	11	11	11	5120	118.1	17.6
10	7	6	6	6	3300	120.0	17.5
11	4	4	4	4	3070	119.6	18.5
12	10	9	8	8	4480	118.0	18.7
13	4	4	4	4	2760	124.0	18.8
14	4	3	0	0	2300	131.2	18.5
15	10	9	8	9	4260	126.3	19.2
16	11	11	7	8	5160	119.7	18.7
17	10	10	8	9	4060	121.9	17.9
18	6	6	6	6	3110	123.4	17.9

(words correct)/(words in) = .852

(words correct)/(words out) = .890

(words semantically correct)/(words out) = .919

#In = Number of words in actual (input) phrase

#Out = Number of words in output phrase

#Cor = Number of words correctly identified

#SemCor = Number of words semantically correct (error irrelevant to task)

Length = Duration of phrase in milliseconds

Main = (computation time of main recognition routine)/Length

Aco = (computation time of acoustics module)/Length

TABLE 15

The 18 utterances are shown in Table 16. In each pair the actual utterance is given, followed by the utterance which the **DRAGON** system found as the optimal path in its model. The system correctly recognized 8 of the 18 utterances. If we consider "compare" (in sentence 15) to have the same meaning as "look at", and if we consider "compare A and B" to be equivalent to "compare A with B" (in sentence 9), then 10 of the 18 sentences or 55% are semantically correct. A sophisticated semantic component might be able to correct some of the other errors. Appendix E also shows the correct and estimated utterances for the other two tasks for this implementation

## Utterances for Interactive Formant Tracking Task

- 1) I want to do formant tracking.  
I want to do formant tracking.
- 2) Use a Hamming window of five hundred twelve points.  
Use a Hamming window of five hundred \_\_\_\_\_ points.
- 3) Use utterance number six of file number five.  
Use utterance number six of file number five.
- 4) Increment the window in steps of one hundred points.  
Increment the window in steps of four points.
- 5) For each window, display the Fourier spectrum.  
For each window, display the formant tracks.
- 6) Compute the LPC smoothed spectrum using the autocorrelation method.  
Compute the LPC smoothed spectrum using the autocorrelation method.
- 7) Compute the roots of the inverse filter using Bairstow's method.  
Compute the roots of the inverse filter using Bairstow's method.
- 8) Display the imaginary part of the roots.  
Display the imaginary part of the roots.
- 9) I want to compare the autocorrelation method with the covariance method.  
I want to compare the autocorrelation method and the covariance method.
- 10) Increment the window by one hundred points.  
Increment the window by one \_\_\_\_\_ points.
- 11) Display the FFT spectrum.  
Display the FFT spectrum.
- 12) Use a Hanning window of two hundred fifty-six points.  
Use a Hanning window of two hundred \_\_\_\_\_ six hertz.
- 13) Display the FFT spectrum.  
Display the FFT spectrum.
- 14) Compute the Hilbert transform.  
Use two points.
- 15) I want to look at image enhancement with different parameters.  
I want to compare image enhancement with different parameters.
- 16) Display the spectrogram with a pre-emphasis of six decibels per octave.  
Display the spectrogram to a pre-emphasis of six thousand five hertz.
- 17) Use a ceiling of thirty with a floor of zero.  
Use a ceiling of ten to a floor of zero.
- 18) For each utterance display the spectrogram.  
For each utterance display the spectrogram.

TABLE 16

of DRAGON, and 9 sentences in the AP News task and 8 sentences in the formant task for an

earlier version of DRAGON.

By considering the specific words which the system identified incorrectly, it is possible to gain some insight about the places at which the model is weakest and/or the task is most difficult. The errors for the FORMANT task are given in Table 17.

#### ERRORS IN FORMANT TASK

	actual phrase	substitution
2)	twelve	_____
4)	one hundred	four
5)	Fourier spectrum	formant tracks
9)	with	and
10)	hundred	_____
12)	fifty	_____
	points	hertz
14)	(entire sentence missed)	
15)	look at	compare
16)	with	to
	decibels per octave	thousand five hertz
17)	thirty with	ten to

TABLE 17

Six of the twelve places at which errors occur involve numbers. It is not surprising that numbers are the greatest point of weakness. In any context in which a number can occur, any number less than one billion is considered grammatical (sometimes including zero). The system has no source of knowledge other than acoustics to select which of the one billion possible numbers was actually



spoken. Recognizing a number imbedded in continuous speech from acoustic information alone is a difficult task, and the one-out-of-a-billion selection is usually beyond the ability of this simple general system.

The prepositions and conjunctions are the second greatest source of errors. These function words are usually short and unstressed, so the acoustic information is very unreliable. Previous speech recognition studies ([T3]) have shown that short words are missed more often than long words, and that unstressed function words are missed even more often than other short words. On the other hand, it is often possible to "understand" a sentence as a whole without correctly identifying all the prepositions and conjunctions.

Of the remaining errors, two are caused entirely by a weakness in the model. The original BNF grammar specifies that a "window" length (sentence (12)) be given as a number of "points," and a "pre-emphasis" be specified in "decibels per octave" or "db per octave." In translating the BNF grammar to a finite state grammar, these restrictions were removed. These restrictions could have been retained in the finite state grammar, but only by having a larger state space. Six copies of the number sub-grammar would suffice to distinguish the uses of number with different right contexts ("points", "hertz", <res-unit>, "coefficients", "per octave", and end-of-phrase). If these two errors were corrected with an expanded grammar, all of the remaining semantically important errors would be numbers, except for sentences (5) and (14).

The current simple implementation of the **DRAGON** system has been designed merely to demonstrate the practicality and power of its general concepts. Clearly many improvements are possible. For example, the acoustic data could be pre-processed and organized into phone-like segments. Then the calculations represented by equations (II.18) and (II.20) would only need to be done for each segment rather than for each 10 millisecond acoustic parameter sample. This reformulation would speed up the calculation in the main recognition program by a factor of about three or four. Especially for larger tasks, substantial savings in computation time can be achieved by employing less than a complete optimal search. A careful study must be done to determine the trade-offs between performance and amount of computation with sub-optimal techniques. More sophisticated models are possible for the knowledge sources, which ought to improve the perform-

ance although they would generally increase the amount of computation. A true probabilistic grammar would allow a statistical representation of some semantics as well as a more accurate grammar.

## CONCLUSIONS

Let's review the major features of the **DRAGON** speech recognition system and consider how these features influence the performance of this implementation. Some of the features of the **DRAGON** system contribute to its simplicity and ease of implementation, while others give it its power.

### (1) Generative form of the model

The fact that the abstract model represents knowledge sources in a generative form made **MAKGRM** and **MAKDIC** much simpler to implement. The **DRAGON** network explicitly represents a finite state grammar. Although the underlying stochastic process is assumed to be Markovian, sufficient context is included in the formulation of the state space so that the finite state grammar is represented exactly. It is not necessary to make any compromise to represent the inverse of grammatical productions based on local context. In this regard the **DRAGON** system shares some of the advantages of the top-down recognition systems. On the other hand, the present implementation is limited to a finite state space, so **MAKGRM** translates any context-free grammar to a related finite state grammar.

### (2) Hierarchical arrangement of knowledge sources

The arrangement of the knowledge sources into a conceptual hierarchy simplifies the implementation of the **DRAGON** system by allowing a modularity that separates the details of the representation of the knowledge sources from the recognition program. In this simple implementation this modularity is expressed in the fact that **MAKGRM**, **MAKDIC**, **MAKNET**, **GETPRB**, and **DRAGON** are independent programs with well-defined communication. In a more sophisticated implementation the modularity could progress even further and would be even more valuable.

The hierarchical arrangement is also reflected in the sparseness of the transition matrix for the integrated process. This sparseness has played an important role in this implementation of the **DRAGON** system. The explicit network representation allows us to directly access the non-zero entries of the transition matrix, thus avoiding unnecessary computations in the formal equation (II.18). The bit-packed representation of the back pointers allows the entire recognition computation to be performed using core memory.

### (3) Integrated network representation

This implementation of the **DRAGON** system integrates the segmentation and labeling into the hierarchy, so the optimal search algorithm performs the segmentation and labeling along with the word identification and parsing. A price is paid in terms of the amount of computation time because the underlying Markov process steps once for every 10 millisecond segment, rather than once for every phone-like segment. However, even this simple implementation can show the advantage of an integrated system compared to a system attempting to make decisions based on any one knowledge source in isolation. The help which the recognition procedure gets from other sources of knowledge allows the segmentation and labeling to be done reliably even with the crude acoustic parameters and simple metric used in GETPRB.

### (4) General theoretical framework

The presence of a general theoretical framework greatly simplified the implementation of the **DRAGON** system. It is this feature which has made it possible to construct a complete speech recognition system with limited manpower. It has been necessary to compromise the theoretical framework in a few places (notably the GETPRB procedure and the lexical model), but in general there has been much less special purpose programming than there would have been without the abstract model. The abstract model has been sufficiently flexible that very few compromises have been necessary in deciding what knowledge to represent (with the important exception of semantic knowledge, which has been omitted entirely). The only significant example is that the grammar represented in the network is a finite state grammar rather than a general context-free grammar. This restriction has not been a significant handicap for the 5 tasks which have been implemented so far.

### (5) Optimal stochastic search

The optimal search strategy is probably the most unique feature of the **DRAGON** system. It has a significant disadvantage in requiring extra computation. However, the special features of the Markov model allow an optimal search algorithm for which the amount of computation is not nearly as great as might naively be supposed. This implementation of the **DRAGON** system, despite many drawbacks and simplifications, has shown that an optimal search is possible and practical.

The advantages of optimal stochastic search come from avoiding early decisions which might be wrong. By extending all partial paths in parallel we are, in effect, delaying all decisions until all context, past and future, has been considered. The amount of "context" is determined by the formulation of the Markov state space. In the highly stylized grammars used in these interactive computer tasks, the "context" often reaches all the way back to the beginning of the utterance. Thus the optimal search strategy may delay the decision about the first word of the utterance until the effect of this decision on the entire sentence has been considered.

### FUTURE WORK

There are many improvements which can be made even within the framework of the current system. The introduction of a sophisticated acoustic preprocessor, while departing from the philosophy of building an entire system from the same abstract model, would result in a significant increase in computational speed. The techniques for using such a preprocessor within the general **DRAGON** system are described in Chapter III (equations (9), (10), and (11)).

The lexical model could be improved either by introducing phonological rules or by using the general lexical model of Chapter III. Either model could be trained using the procedure represented by equations (21) and (22) of Chapter II.

The syntactic-semantic model would be improved by introducing estimates of the conditional probability distributions into the grammar. Given a task with a known grammar, this estimation mainly involves the collection of statistics for a large corpus of utterances from a dialogue in the inter-active computer task. Even for a task with an unspecified grammar, an attempt can be made

to approximate the grammar using the re-estimation procedure of equations (21) and (22) of Chapter II.

The assumption of a finite state space (and hence a finite state grammar) is not essential. Markov processes may have infinite state spaces, and much of the theory used here carries through. There are serious problems which must be solved to obtain a practical implementation, but they are not insurmountable. For example, equation (18) of Chapter II can be generalized to apply to an arbitrary context-free grammar, at the expense of making the number of computations proportional to  $T^3$  rather than to  $T$ . By segmenting the utterance into syllables,  $T$  would be the number of syllables and  $T^3$  might not be too large.

What general implications can be drawn from the results of the **DRAGON** speech recognition system? The **DRAGON** system differs from most other speech recognition systems in three important ways: (1) the use of Markov models, (2) the use of the same abstract model to represent each of the knowledge sources, and (3) the optimal search strategy.

Since the state space can be formulated to include specific context information, the assumption of the Markov property in the models is not so much an assumption as it is a prescription to be followed in the formulation of the state space. The results for this simple implementation demonstrate that this prescription can be followed well enough to get reasonable recognition while keeping the state space of manageable size. However, because the **FORMANT** task took 173.8 times real time and because the size of the **DRAGON** network grows with the size of the vocabulary, there is a significant area for future research. Techniques need to be developed which can more efficiently represent more complex tasks.

The use of a general abstract model has greatly facilitated the development of the **DRAGON** system and has important implications. Lowerre ([L3]) has been able to analyze the main recognition program to produce an optimized program which produces identical results but is much faster than the original program. Work is being done to adapt the **DRAGON** system to run on a minicomputer. Newell ([N3]) has suggested that the simplicity of the **DRAGON** system would allow it to be used as a "benchmark" system. Any more sophisticated system must justify its greater complexity by recognizing speech either in less time or more accurately than the **DRAGON**

system.

A major motivation for constructing the **DRAGON** system has been to demonstrate that speech recognition based on complete optimal search is practical. Clearly, however, a complete search is not the most efficient procedure. The most important area for future research is to develop techniques such that the complete Markov search is an upper bound on the amount of computation, but such that much less computation time is used exploring parallel paths when the correct path is clear.



00100	"AA"	- AA
00200	"AE"	- AE
00300	"AH"	- AH
00400	"AO"	- AO
00500	"AW"	- AA UH
00600	"AY"	- AA IH
00700	"B"	- B IY
00800	"CH"	- SH
00900	"D"	- D IY
01000	"EH"	- EH
01100	"ER"	- ER ER
01200	"EY"	- EH IH
01300	"F"	- EH F
01400	"FILLER"	-
01500	"G"	- G IY
01600	"HH"	- EH IH - SH
01700	"I"	- AA IH
01800	"IH"	- IH
01900	"IY"	- IY
02000	"JH"	- SH
02100	"K"	- K EH IH
02200	"L"	- EH L
02300	"M"	- EH M
02400	"N"	- EH N
02500	"NULL"	-
02600	"NX"	- IH NX
02700	"OW"	- OW
02800	"OY"	- AO IH
02900	"P"	- P IY
03000	"R"	- AA ER
03100	"S"	- EH S
03200	"SH"	- SH
03300	"T"	- T IY
03400	"UH"	- UH
03500	"UW"	- UW
03600	"V"	- V IY
03700	"WH"	- WH
03800	"Y"	- W AA IH
03900	"Z"	- S IY
04000	"ZH"	- SH
04100	'S	- S
04200	A	- AX
04300	ABOUT	- AX - B AH - T
04400	ABOVE	- AX - B AH V
04500	ABSOLUTE	- AE - B S AX L UW - T
04600	ABSOLUTE	- AE - B S OW L UW - T
04700	ACOUSTIC	- AX - K UW S - T IH - K
04800	ADC	- EH IH - D IY S IY
04900	ADD	- AE - D
05000	ADVANCED	- AE - D V AE N - S - T
05100	AFRAID	- AX F ER EH IH - D
05200	AIRPLANE	- EH ER - P L AE IH N
05300	AIRPLANES	- EH ER - P L EH IH N - S
05400	ALL	- AO L
05500	ALPHA	- AH L F AX
05600	AN	- AE N
05700	AN	- AX N
05800	ANALYSIS	- AX N AE L IH S IH S
05900	ANALYZE	- AE N L AA IH S
06000	AND	- AX N - D
06100	ANESTHETIZED	- AX N EH S - T AX S AX - S - D
06200	ANOTHER	- AH N AH F ER
06300	ARE	- AA ER AX
06400	AS	- AE S
06500	ASPIRATED	- AE S - P IH ER EH IH - T EH - D

06600	ASPIRATION	- AE S - P IH ER AA IH SH AX N
06700	ASTHMA	- AE S M AX
06800	AT	- AE - T
06900	ATAL	- AH - T AA L
07000	ATTACHED	- AA - T AE - SH - T
07100	AUTOCORRELATION	- AO - T OW - K AO ER EH L EH IH SH AX N
07200	AWFUL	- AO F AH L
07300	BABY	- B EH IH - B IY
07400	BACK	- B AE - K
07500	BACKED	- B AE - K - O
07600	BAO	- B AE - O
07700	BAIRSTON	- B AE ER S - T OW
07800	BAKER	- B EH IH - K ER
07900	BALL	- B AA L
08000	BALLED	- B AA L - O
08100	BALLS	- B AA L S
08200	BANOWIOTH	- B AE N - D W IH - O F
08300	BARRED	- B AA ER - O
08400	BECOMES	- B AX - K AH M S
08500	BEEN	- B AX N
08600	BEGINNING	- B IY - G IH N IH NX
08700	BENT	- B EH N - T
08800	BETA	- B EH IH - T AH
08900	BIRO	- B ER - O
09000	BISHOP	- B IH SH AX - P
09100	BISHOP'S	- B IH SH AX - P S
09200	BLACKWELL	- B L AE - K W EH L
09300	BLEEDING	- B L IY - O IH NX
09400	BOTTLE	- B AA - T L
09500	BOUNDARY	- B AE AA N - O ER IY
09600	BOY	- B AO IH
09700	BURST	- B ER S - T
09800	BY	- B AA IH
09900	CALCULATE	- K AE L - K Y UW L EH IH - T
10000	CAPTURES	- K AE - P - SH ER S
10100	CASTLE	- K AE S L
10200	CASTLES	- K AE S L S
10300	CASTRATED	- K AE S - T ER EH IH - T AX - O
10400	CAT	- K AE - T
10500	CATEGORY	- K AE - T AX - G AO ER IY
10600	CEILING	- S IY L IH NX
10700	CENTER	- S EH N - T ER
10800	CENTISECONOS	- S EH N - T IH S EH - K AX N - O S
10900	CENTRALIZED	- S EH N T ER L AA IH S - O
11000	CEPSTRAL	- K EH - P S - T ER L
11100	CEPSTRALLY	- K EH - P S - T ER L IY
11200	CEPSTRUM	- K EH - P S - T ER AH M
11300	CHANGE	- SH EH N - G
11400	CHECK	- SH EH - K
11500	CHEST	- SH EH S - T
11600	CHICKEN-POX	- SH IH - K AX N - P AA - K S
11700	CHINA	- SH AA IH N AX
11800	CHURCH	- SH ER - SH
11900	CIGARETTES	- S IH - G ER EH - T S
12000	CIRCUMCISED	- S AX ER - K AH M S AX - S - O
12100	CLOUDY	- K L AA UW - O IY
12200	CLUSTERING	- K L AH S - T ER IH NX
12300	COEFFICIENTS	- K OW EH F IH SH IH N - T S
12400	COMMA	- K AH M AX
12500	COMPARE	- K AH M - P AE ER
12600	COMPILE	- K AH M - P AA IH L
12700	COMPUTE	- K AH M - P Y UW - T
12800	CONSIDER	- K AH N - S IH - O ER
12900	CONSTRUCTION	- K AX N - S - T ER AH - K SH AX N
13000	CONTINUOUS	- K AX N - T IH N Y UW AX S

13100	COVARIANCE	- K DH V AE ER IY AE N - S
13200	CRAMPS	- K ER AE M - P S
13300	CREAM	- K ER IY M
13400	CREF	- K ER EH F
13500	CURSOR	- K ER S ER
13600	CUTOFF	- K AH - T AD F
13700	CYCLES	- S AA IH - K L S
13800	DB	- D IY - B IY
13900	DEAD	- D EH - D
14000	DEBUG	- D IY - B AA - G
14100	DEBUGGING	- D IY - B AX - G IH NX
14200	DECIBELS	- D EH S IH - B EH L S
14300	DECIMAL	- D EH S M L
14400	DELETE	- D AX L IY - T
14500	DELTA	- D EH L - T AH
14600	DENIALIZED	- D EH N - T L AA IH S - D
14700	DEPRESSED	- D IY - P ER EH S - D
14800	DERIVATION	- D AE ER IH V EH IH SH AX N
14900	DESIGNING	- D AX S AA IH N IH NX
15000	DESIRE	- D IH S AA IH ER
15100	DETAIL	- D IY - T EH IH L
15200	DIO	- D IH - D
15300	DIFFERENT	- D IH F ER N - T
15400	DIGITAL	- D IH - G IH - T L
15500	DISPLAY	- D AX S - P L EH IH
15600	DIVIDE	- D IH V AA IH - D
15700	DIVIDES	- D IH V AA IH - D S
15800	DIZZINESS	- D IH S IY N AX S
15900	DO	- D UH
16000	DOG	- D AD - G
16100	DOING	- D UH IH NX
16200	DOMAIN	- D DH M EH IH N
16300	DONE	- D AH N
16400	DOUBLE-U	- D AH - B L Y UH
16500	DOHN	- D AA UH N
16600	DRINK	- D ER IH NX - K
16700	DYNAMIC	- D AA IH N AE M IH - K
16800	EACH	- IY - T SH
16900	EASY	- IY S IY
17000	EDITING	- EH - D IH - T IH NX
17100	EIGHT	- EH IH - T
17200	EIGHTEEN	- EH IH - T IY N
17300	EIGHTY	- EH IH - T IY
17400	ELEVATED	- EH L EH V EH IH - T EH - D
17500	ELEVEN	- IY L EH V AX N
17600	EN-PASSENT	- AA N - P AA S AA N
17700	END	- EH N - D
17800	ENHANCEMENT	- AX N HH AE N S - M AX N - T
17900	EPSILON	- EH - P S IH L AA N
18000	ESTIMATION	- EH S - T IH M EH IH SH AX N
18100	EVER	- OH V ER
18200	EXECUTE	- EH - K S AX - K AA UH - T
18300	EXTRA	- EH - K S - T ER AX
18400	FACT	- F AE - K - T
18500	FACTOR	- F AA - K - T AD ER
18600	FANT	- F AA N - T
18700	FAST	- F AE S - T
18800	FATHER	- F AA DH ER
18900	FATHOM	- F AE F AX M
19000	FEATHER	- F EH DH ER
19100	FEATURE	- F IY - T SH ER
19200	FEVER	- F IY V ER
19300	FEVERISH	- F IY V ER IH SH
19400	FFT	- EH F EH F - T IY
19500	FIFTEEN	- F IH F - T IY N

19600	FIFTY	- F IH F - T IY
19700	FILE	- F AA IH L
19800	FILTER	- F IH L - T ER
19900	FILTERED	- F IH L - T ER - D
20000	FINAL	- F AA IH N L
20100	FIND	- F AA IH N - O
20200	FINDING	- F AA IH N - D IH NX
20300	FIRST	- F ER S - T
20400	FIVE	- F AA AX V
20500	FLAP	- F L AE - P
20600	FLOOR	- F L AO ER
20700	FOOL	- F UH L
20800	FOR	- F AO ER
20900	FORMANT	- F AO ER M AE N - T
21000	FOUR	- F AO W ER
21100	FOURIER	- F AO EK IY EH IH
21200	FOURTEEN	- F AO ER - T IY N
21300	FOURTY	- F AO ER - T IY
21400	FRANCE	- F ER AE N - S
21500	FREQUENCY	- F ER IY - K W EH N - S IY
21600	FREQUENTLY	- F ER IY - K W AX N - T L IY
21700	FRICTIONAL	- F ER IH - K SH AX N L
21800	FRONTO	- F ER AH N - T EH - O
21900	FUNCTION	- F AH N - K SH AX N
22000	GAMMA	- G AE M AH
22100	GET	- G EH - T
22200	GETS	- G EH - T S
22300	GIVE	- G IH V
22400	GLOTTAL	- G L AA - T L
22500	GO	- G OH
22600	GOES	- G OH S
22700	GOES-TO	- G OH S - T AX
22800	GOING	- G OH IH NX
22900	GONORRHEA	- G AA N ER IY AX
23000	GRAMMAR	- G ER AE M ER
23100	GRAMMATICAL	- G ER AX M AE - T IH - K L
23200	GRAPHICS	- G ER AE F IH - K S
23300	GRASS	- G ER AE S
23400	HAD	- HH AE - D
23500	HAMMING	- HH AE M IH NX
23600	HANNING	- HH AE N IH NX
23700	HAVE	- HH AE V
23800	HEAD	- HH EH - D
23900	HEADACHES	- HH EH - D IH AX - K S
24000	HEADLINES	- HH EH - O L AA IH N - S
24100	HELLO	- HH EH L OW
24200	HERE	- HH IH ER
24300	HERTZ	- HH ER - T S
24400	HIGH	- HH AA IH
24500	HIJACKING	- HH AA IH - SH AE - K IH NX
24600	HILBERT	- HH IH L - B ER - T
24700	HOSPITALIZED	- HH AA S - P AX L AX S - O
24800	HOW	- HH AA W
24900	HUNDRED	- HH AH N - O ER EH - O
25000	HYPOTHESIS	- HH AA IH - P AA F IH S IH S
25100	I	- AA IH
25200	ICE	- AA IH S
25300	ILL	- IH L
25400	IMAGE	- IH M IH - SH
25500	IMAGINARY	- IH M AE - G IH N AE ER IY
25600	IMMUNIZED	- IH M Y UW N AX S - O
25700	IN	- IH N
25800	INCREMENT	- IH N - K ER AX M EH N - T
25900	INITIAL	- IH N IH SH L
26000	INJURED	- IH N - SH ER - O

26100	INSERT	- IH N - S ER - T
26200	INSTANCE	- IH N - S - T AE N - S
26300	INTERACTIVE	- IH N - T ER AE - K - T IH V
26400	INTO	- IH N - T UW
26500	INVERSE	- IH N V ER S
26600	IS	- AX S
26700	ISRAEL	- IH S ER IY L
26800	IT	- IH - T
26900	ITALURA	- IH - T AH - K ER AH
27000	JAMES	- SH EH IH M S
27100	JUDGE	- SH AH - D - SH
27200	KING	- K IH NX
27300	KING'S	- K IH NX S
27400	KNIGHT	- N AA IH - T
27500	KNIGHT'S	- N AA IH - T S
27600	LABEL	- L EH IH - B L
27700	LABELING	- L EH IH - B L IH NX
27800	LABELS	- L EH IH - B L S
27900	LARYNGEALIZED	- L AA ER IH N - G L AA IH S - O
28000	LEARN	- L ER N
28100	LEFT	- L EH F - T
28200	LENGTH	- L AX NX - F
28300	LESION	- L IY S AX N
28400	LESIONS	- L IY S AX N - S
28500	LET	- L EH - T
28600	LILY	- L IH L IY
28700	LINEAR	- L IH N IY ER
28800	LION	- L AA IH UW N
28900	LIP	- EH L AA IH - P IY
29000	LIST	- L IH S - T
29100	LITERAL	- L IH - T ER L
29200	LOAD	- L OH - D
29300	LOCALIZED	- L OH - K L AA IH S - D
29400	LOG	- L AO - G
29500	LOGARITHM	- L AO - G AE ER IH F M
29600	LONG	- L AO NX
29700	LOOK	- L UW - K
29800	LOU	- L OH
29900	LOWERED	- L OW ER - D
30000	LPC	- EH L - P IY S IY
30100	MARKEL	- M AA ER - K L
30200	MARKING	- M AA ER - K IH NX
30300	MATE	- M EH IH - T
30400	MAX	- M AE - K S
30500	MAY	- M EH IH
30600	ME	- M IY
30700	MENGLES	- M IY S L S
30800	MEASURE	- M EH SH ER
30900	METHOD	- M EH F AH - D
31000	METHODS	- M EH F AH - O S
31100	MICROSECONOS	- M AA IH - K ER OW S EH - K AX N - D S
31200	MILD	- M AA IH L - O
31300	MILLION	- M IH L IH AX N
31400	MILLISECONOS	- M IH L IH S EH - K AX N - D S
31500	MIN	- M IH N
31600	MINUS	- M AA IH N AH S
31700	MOD	- M AH - D
31800	MODIFIER	- M AA - O IH F AA IH ER
31900	MON	- M AA M
32000	MOVE	- M UH V
32100	MOVES	- M UH V S
32200	MOVES-TO	- M UH V S - T AX
32300	MUCH	- M AA - SH
32400	MUMPS	- M AX M - P S
32500	MURDER	- M ER - D ER

32600	NASALIZED	- N EH IH S L AA IH S - O
32700	NAUSEA	- N AO AH SH AX
32800	NEGAT	- N AX - G EH IH - T
32900	NETWORK	- N EH - T W ER - K
33000	NEW	- N UH
33100	NEWTON	- N UH - T AX N
33200	NINE	- N AA IH N
33300	NINETEEN	- N AA IH N - T IY N
33400	NINETY	- N AA IH N - T IY
33500	NIXON	- N IH - K S AX N
33600	NOBODY	- N OU - B AH - D IY
33700	NON-SPEECH	- N AA N - J - P IY - SH
33800	NOH	- N AA UH
33900	NUMBER	- N AH M - B ER
34000	NUMBNESS	- N AH AX M N AX S
34100	NUTS	- N AX - T S
34200	OBOE	- OW - B OW
34300	OCTAL	- AA - K - T L
34400	OCTAVE	- AA - K - T EH V
34500	OF	- AO V
34600	OF	- AX V
34700	OFTEN	- AO AH F AX N
34800	ON	- AO N
34900	ONE	- W AH N
35000	OPERATION	- AH - P ER AE IY SH AX N
35100	OR	- AO ER
35200	ORDER	- AO ER - O ER
35300	OVEREAT	- OW V ER IY - T
35400	PAIN	- P AX IH N
35500	PAINS	- P AX IH N S
35600	PALATALIZED	- P AE L AE - T L AA IH S - D
35700	PARAMETER	- P AX ER AE M EH - T ER
35800	PARAMETERS	- P ER AE M AX - T ER S
35900	PART	- P AA ER - T
36000	PASS	- P AE S
36100	PAIN	- P AO N
36200	PEAK	- P IY - K
36300	PEAKS	- P IY - K S
36400	PER	- P ER
36500	PERIOD	- P IH ER IY AX - O
36600	PHONE	- F OW N
36700	PHONEME	- F OW N IY M
36800	PHONEMIC	- F AX N IY M IH - K
36900	PHONETIC	- F AX N EH - T IH - K
37000	PHRASE	- F ER EH IH S
37100	PICKING	- P IH - K IH NX
37200	PITCH	- P IH - T SH
37300	PLOT	- P L AA - T
37400	PLUS	- P L AH S
37500	POINTS	- P AO IH N - T S
37600	POP	- P AA - P
37700	POSITION	- P AX S IH SH AX N
37800	POSITIONS	- P AX S IH SH AX N - S
37900	POST-EMPHASIS	- P OW S - T EH M F AH S IH S
38000	POT	- P AA - T
38100	POWER	- P AA W ER
38200	PRE-EMPHASIS	- P ER IY EH M F AH S IH S
38300	PREDICTION	- P ER IY - D IH - K SH AX N
38400	PREDICTIVE	- P ER AX - D IH - K - T IH V
38500	PRESENT	- P ER EH S EH N - T
38600	PRIMARY	- P ER AA IH M EH ER IY
38700	PRONY	- P ER OW N IY
38800	PROTOCOL	- P ER OW - T OW - K AO L
38900	PUP	- P AH - P
39000	PUT	- P UH - T



39100	O	- K AA UH
39200	QUEEN	- IH IY N
39300	QUEEN'S	- WH IY N - S
39400	RABINER	- ER AH - B IH N ER
39500	RAISED	- ER EH IH S - D
39600	RAPE	- ER AE IH - P
39700	RATING	- ER EH IH - T IH NX
39800	REAL	- ER IY L
39900	RECTANGULAR	- ER EH - K - T EH IH N - G Y UW L AA ER
40000	REDUCED	- ER IH - D UW S - T
40100	RELEASED	- ER IH L IY S - T
40200	REQUEST	- ER IY - K W IH S - T
40300	RESOLUTION	- ER EH S OW L UW SH AX N
40400	RETRACTED	- ER IY - T ER AE - K - T EH - D
40500	RETROFLEXED	- ER EH T ER OW F L EH - K S - D
40600	RIGHT	- ER AA IH - T
40700	ROAR	- ER OW ER
40800	ROBINSON	- ER AA - B IH N - S AH N
40900	ROOK	- ER UH - K
41000	ROOK'S	- ER UH - K S
41100	ROOT	- ER UH - T
41200	ROOTS	- ER UW - T S
41300	ROSES	- ER OW S IH S
41400	ROUNDED	- ER AA UH N - D EH - D
41500	RUSSIA	- ER AX SH AX
41600	SAY	- S EH IH
41700	SCALE	- S - K EH IH L
41800	SCHAFER	- SH EH IH F ER
41900	SCHUH	- SH W AA
42000	SECOND	- S EH - K AH N - D
42100	SECONDARY	- S EH - K AH N - D EH ER IY
42200	SECTION	- S EH - K SH AX N
42300	SEE	- S IY
42400	SEGMENT	- S EH - G M AX N - T
42500	SLGUE	- S EH - G W EH IH
42600	SENTENCE	- S EH N - T EH N - S
42700	SERIOUS	- S IH ER IY AX S
42800	SEVEN	- S EH V AX N
42900	SEVEN	- S EH V EH N
43000	SEVENTEEN	- S EH V EH N - T IY N
43100	SEVENTY	- S EH V EH N - T IY
43200	SEVERE	- S AX V IH ER
43300	SEX	- S EH - K S
43400	SHARP	- SH AH ER - P
43500	SHORT	- SH AD ER - T
43600	SHOULD	- SH UH - D
43700	SHOW	- SH OW
43800	SICK	- S IH - K
43900	SIDE	- S AA IH - D
44000	SILENCE	- S AA IH L EH N - S
44100	SIMULATION	- S IH M Y UW L EH IH SH AX N
44200	SING	- S IH NX
44300	SISTER	- S IH S - T ER
44400	SIT	- S IH - T
44500	SIX	- S IH - K S
44600	SIXTEEN	- S IH - K S - T IY N
44700	SIXTY	- S IH - K S - T IY
44800	SLASH	- S L AE SH
44900	SNOKE	- S M OW - K
45000	SMOOTHED	- S M UH F - D
45100	SMOOTHING	- S M UW F IH NX
45200	SPEAKER	- S - P IY - K ER
45300	SPECIFICATION	- S - P EH S IH F IH - K EH IH SH AX N
45400	SPECTRAL	- S - P EH - K - T ER L
45500	SPECTROGRAM	- S - P EH - K - T ER OW - G ER AE N

45600	SPECTRUM	- S - P EH - K - T ER AX M
45700	SPEECH	- S - P IY - T SH
45800	START	- S - T AA ER - T
45900	STARTING	- S - T AA ER - T IH NX
46000	STATE	- S - T EH IH - T
46100	STEADY	- S - T EH - D IY
46200	STEPS	- S - T EH - P S
46300	STOP	- S - T AA - P
46400	STORE	- S - T AO ER
46500	STORIES	- S - T AO ER IY S
46600	STRESS	- S - T ER EH S
46700	SUB-PHONETIC	- S AH - B F AX N EH - T IH - K
46800	SUB-SEGMENT	- S AH - B S EH - G M EH N - T
46900	SUDDEN	- S AH - D AX N
47000	SUMMARY	- S AX M ER IY
47100	SURGERY	- S ER - SH ER IY
47200	SYLLABIC	- S IH L AE - B IH - K
47300	SYMBOL	- S IH M - B AO L
47400	SYNTHESIS	- S IH N F AX S IH S
47500	TALE	- T EH IH - K
47600	TALES	- T EH IH - K S
47700	TASK	- T AE S - K
47800	TELL	- T EH L
47900	TEN	- T EH N
48000	TERTIARY	- T ER SH IY EH ER IY
48100	TESTING	- T EH S - T IH NX
48200	THAT	- DH AE - T
48300	THE	- DH AX
48400	THETA	- F EH IH - T AX
48500	THIN	- F IH N
48600	THIRD	- F ER - D
48700	THIRTEEN	- F ER - T IY N
48800	THIRTY	- F ER - T IY
48900	THORN	- F AO ER N
49000	THOUSAND	- F OW S AE N - D
49100	THREE	- F ER IY
49200	TIME	- T AA IH M
49300	TIMES	- T AA IH M S
49400	TITLE	- T AA IH - T L
49500	TO	- T AX
49600	TRACKING	- T ER AE - K IH NX
49700	TRACIS	- T ER AE - K S
49800	TRAIN	- T ER EH IH N
49900	TRANSCRIPTION	- T ER AE N - S - K ER IH - P SH AX N
50000	TRANSFORM	- T ER AE N - S F AO ER M
50100	TRANSITION	- T ER AE N - S IH SH AX N
50200	TRIANGULAR	- T ER AA IH EH IH N - G Y UW L AA ER
50300	TRILLED	- T ER IH L - D
50400	TUBERCULOSIS	- T UH - B ER - K Y UW L OW S AX S
50500	TWELVE	- T U EH L V
50600	TWENTY	- T W EH N - T IY
50700	TWO	- T UH
50800	TWO	- T W UH
50900	UN-STRESSED	- AH N - S - T ER EH S - D
51000	UNROUNDED	- AH N ER AA UH N - D EH - D
51100	UNTIL	- AX N - T IH L
51200	URINE	- Y ER AX N
51300	US	- AH S
51400	USE	- Y UH S
51500	USING	- Y UH S IH NX
51600	UTTERANCE	- AH - ER EH N - S
51700	VALUE	- V AE L Y UW
51800	VERL	- V IY L
51900	VELARIZED	- V IY L AA ER AA IH S - D
52000	VIETNAM	- V IH EH - T N AE M

52100	VOICED	- V AO IH S - D
52200	VOICELESS	- V AO IH S L EH S
52300	W	- O AA - B L AA UM
52400	WAGON	- W AE - G AX N
52500	WANT	- W AA N - T
52600	WAR	- W AO ER
52700	WATERGATE	- W AO - T ER - G AE IH - T
52800	WAVEFORM	- W EH IH V F AO ER M
52900	WE	- H IY
53000	WEIGH	- W AO AX
53100	WEIR	- H ER
53200	WHAT	- W AH - T
53300	WHEN	- W AX N
53400	WHERE	- W HE ER
53500	WHICH	- WH IH - SH
53600	WINDOW	- W IH N - O OW
53700	WITH	- W IH F
53800	WORO	- W ER - O
53900	X	- EH - K S
54000	Y	- W AA IH
54100	YELLOW	- Y EH L OH
54200	YES	- Y EH S
54300	YOU	- Y AX
54400	YOUR	- Y ER
54500	Z	- S IY
54600	ZERO	- S IH ER OW
54700	ZOO	- S UW
54800	[	-
54900	]	-

```

00100 ; SUB-GRAMMAR FOR FORMANT TRACKING SUB-TASK.
00200
00300 <f!form-sent>::= [ <f!request> ]
00400
00500 <f!request>::= <f!desire-sent>
00600 <f!param-sent>
00700
00800 <f!desire-sent>::= I WANT TO DU <f!task>
00900
01000 <f!task>::=
01100 FORMANT TRACKING
01200 TIME DOMAIN ANALYSIS
01300 PITCH MARKING
01400 PHONETIC BOUNDARY MARKING
01500 PHONETIC LABELING
01600 PHONETIC TRANSCRIPTION
01700 ACOUSTIC FEATURE LABELING
01800 GRAMMATICAL CATEGORY DERIVATION
01900 GRAMMAR SPECIFICATION
02000 NETWORK EDITING
02100 PARAMETER TESTING
02200 DEBUGGING
02300 SIMULATION
02400 HYPOTHESIS RATING
02500 FACTOR ANALYSIS
02600 CLUSTERING
02700 DISPLAY CONSTRUCTION
02800 SPEECH SYNTHESIS
02900 DIGITAL FILTER DESIGNING
03000 <f!param-sent>::= <f!command>
03100 <f!intro><f!command>
03200
03300 <f!command>::= USE <f!param-phr>
03400 <f!compute><f!func-phr>
03450 <f!compute><f!func-phr> USING <f!meth-type> METHOD
03500 <f!plot><f!plot-item>
03600 <f!compare><f!alter-list>
03700 INCREMENT THE <f!incre-spec> <f!incre-prep> <f!nine-digit> POINTS
03800
03900 <f!intro>::= I WANT TO
04000 FOR EACH <f!iter-item>
04100
04200 <f!iter-item>::=
04300 PHRASE
04400 PHONE
04500 PHONEME
04600 SEGMENT
04700 WINDOW
04800 FUNCTION
04900 TIME
05000 POSITION
05100 SENTENCE
05200 UTTERANCE
05300 <f!param-phr>::= <f!param-spec>
05400 <f!param-phr><f!prep><f!param-spec>
05500
05600 <f!param-spec>::=
05700 FILE NUMBER <f!nine-digit>
05800 UTTERANCE NUMBER <f!nine-digit>
05900 A <f!wind-type> WINDOW OF <f!nine-digit> POINTS
06000 A <f!freq-spec> OF <f!nine-digit> HERTZ

```

06200		A <fres-type> RESOLUTION OF <fnine-digit><fres-unit>
06300		<fnine-digit> COEFFICIENTS
06400		AN ORDER OF <fnine-digit>
06500		START TIME <fnum>
06600		END TIME <fnine-digit>
06700		A <femph-type> OF <fnine-digit><fdb> PER OCTAVE
06800		A SCALE FACTOR OF <fnine-digit>
06900		A FLOOR OF <fnum>
07000		A CEILING OF <fnine-digit>
07100		
07200	<flprop>::=	OF
07300		TO
07400		WITH
07500		ON
07700		
07800	<flwind-type>::=	HAMMING
07900		HANNING
08000		BLACKWELL
08100		RECTANGULAR
08200		TRIANGULAR
08300		
08400	<flfreq-spec>::=	FREQUENCY
08500		<flfreq-type> FREQUENCY
08600		BANDWIDTH
08700		
08800	<flfreq-type>::=	CENTER
08900		CUTOFF
09000		LOW PASS
09100		HIGH PASS
09200		
09300	<flmeth-type>::=	<fname> 'S
09500		THE <flmeth-kind>
09600		
09700	<fname>::=	ITAKURA
09800		MARKEL
09900		PRONY
10000		ATAL
10100		ROBINSON
10200		SCHAFER AND RABINER
10300		FANT
10400		NEWTON
10500		BAIRSTOW
10600		
10700	<flmeth-kind>::=	AUTOCORRELATION
10800		COVARIANCE
10900		PEAK PICKING
11000		ROOT FINDING
11100		
11200	<fres-type>::=	TIME
11300		FREQUENCY
11400		
11500	<fres-unit>::=	HERTZ
11600		CYCLES PER SECOND
11700		MICROSECONDS
11800		MILLISECONDS
11900		CENTISECONDS
12000		POINTS
12100		
12200	<femph-type>::=	PRE-EMPHASIS
12300		POST-EMPHASIS

12400		
12500	<f!db>::=	DECIBELS
12600		DB
12700		
12800	<f!compute>::=	COMPUTE
12900		CALCULATE
13000		FIND
13100		GET
13200		TAKE
13300		CONSIDER
13400		
13800	<f!func-phr>::=	THE <f!comp-func>
13900		THE AUTOCORRELATION FUNCTION
14000		THE COVARIANCE FUNCTION
14100		THE FFT
14200		THE FAST FOURIER TRANSFORM
14300		THE FOURIER TRANSFORM
14400		THE HILBERT TRANSFORM
14600		THE LINEAR PREDICTION COEFFICIENTS
14700		THE LINEAR PREDICTION FILTER
14800		THE INVERSE FILTER
14900		THE SPECTRUM
15000		THE CEPSTRUM
15100		THE <f!spec-adj> SPECTRUM
15150		THE ROOTS
15200		
15300	<f!comp-func>::=	<f!func-part>
15400		<f!func-part> OF <f!func-phr>
15500		
15600	<f!func-part>::=	ROOTS
15700		PEAKS
15800		IMAGINARY PART
15900		REAL PART
16000		LOGARITHM
16100		ABSOLUTE VALUE
16200		
16300	<f!plot>::=	PLOT
16400		DISPLAY
16500		SHOW
16600		
16700	<f!plot-item>::=	THE SPECTROGRAM
16710		THE SPECTROGRAM <f!prep><f!param-phr>
16800		THE WAVEFORM
16900		THE FORMANT TRACKS
17000		THE FUNCTION
17100		<f!func-phr>
17200		
17300	<f!spec-adj>::=	SMOOTHED
17400		<f!smth-meth> SMOOTHED
17500		<f!spec-meth>
17600		
17700	<f!spec-meth>::=	CEPSTRAL
17800		LINEAR PREDICTIVE
17900		INVERSE FILTERED
18000		FFT
18100		FAST FOURIER TRANSFORM
18200		FOURIER
18300		
18400	<f!smth-meth>::=	CEPSTRALLY
18500		LINEAR PREDICTION



18600		INVERSE FILTER
18700		LPC
18800		
18900	<f!compare>::=	COMPARE
19000		LOOK AT
19100		CONSIDER
19200		
19300	<f!alter-list>::=	<f!meth-type> METHOD <f!meth-conj><f!meth-type> METHOD
19400		ANOTHER METHOD OF <f!form-task>
19500		<f!form-task> METHODS
19600		<f!form-task> WITH DIFFERENT PARAMETERS
19700		
19800	<f!meth-conj>::=	AND
19900		WITH
20000		
20100	<f!form-task>::=	FORMANT ESTIMATION
20200		SPECTRAL SMOOTHING
20300		IMAGE ENHANCEMENT
20400		ROOT FINDING
20500		LINEAR PREDICTION
20600		
20700	<f!incrc-prep>::=	BY
20800		IN STEPS OF
20900		
21000	<f!incrc-spec>::=	WINDOW
21100		STARTING TIME
21200		
21300	; This is the number sub-grammar.	
21400	; It is used by most of the task sub-grammars.	
21500		
21600	<f!num>::=	<f!nine-digit>
21700		ZERO
21800		
21900	<f!nine-digit>::=	<f!six-digit>
22000		<f!three-digit> MILLION <f!six-digit>
22100		
22200	<f!six-digit>::=	<f!three-digit>
22300		<f!three-digit> THOUSAND <f!three-digit>
22400		
22500	<f!three-digit>::=	<f!two-digit>
22600		<f!digit> HUNDRED <f!two-digit>
22700		<f!digit> HUNDRED
22800		
22900	<f!two-digit>::=	<f!digit>
23000		<f!teen>
23100		<f!tens><f!digit>
23200		<f!tens>
23300		
23400	<f!tens>::=	TWENTY
23500		THIRTY
23600		FOURTY
23700		FIFTY
23800		SIXTY
23900		SEVENTY
24000		EIGHTY
24100		NINETY
24200		
24300	<f!teen>::=	TEN
24400		ELEVEN
24500		TWELVE

24600		THIRTEEN
24700		FOURTEEN
24800		FIFTEEN
24900		SIXTEEN
25000		SEVENTEEN
25100		EIGHTEEN
25200		NINETEEN
25300		
25400	<fdigit>::=	ONE
25500		TWO
25600		THREE
25700		FOUR
25800		FIVE
25900		SIX
26000		SEVEN
26100		EIGHT
26200		NINE

```

00100 ; SYNTAX FOR AP VOICE NEWS QUERY SYSTEM. 28 TERMINAL SYMBOLS (WORDS).
00200
00300 <QUERY>::= [ <REQUEST> ]
00400
00500 <REQUEST>::= LET <PRONOUNA> HAVE <COLL-SUM>
00600 GIVE <PRONOUNB><NOUN-PHRASE>
00700 GIVE <PRONOUNB><COLL-SUM>
00800 TELL <PRONOUNC><COLL-SUM>
00900 TELL <PRONOUNC><QUANTIFIER><NOUN-PHRASE>
01000 TELL <PRONOUNC><TELL-QUAN><SUM-PHRASE>
01100
01200 <COLL-SUM>::= <SUM-PHRASE>
01300 ALL <SUM-PHRASE>
01400 SEX
01500
01600 <SUM-PHRASE>::= THE <SUMMARIESB>
01700 THE <SUMMARIESA> AND <SUMMARIESB>
01800
01900 <SUMMARIESA>::= STORIES
02000 HEADLINES
02100 SUMMARY
02200
02210 <SUMMARIESB>::= STORIES
02220 HEADLINES
02230 SUMMARY
02240
02300 <TELL-QUAN>::= <QUANTIFIER>
02400 ABOUT ALL
02500 ALL
02600
02700 <PRONOUNA>::= ME
02800 US
02900
02910 <PRONOUNB>::= ME
02920 US
02930
02940 <PRONOUNC>::= ME
02950 US
02960
03000 <QUANTIFIER>::= ALL ABOUT
03100 ABOUT
03200
03300 <NOUN-PHRASE>::= <NOUNA> AND <NOUNB>
03400 <NOUNA> OR <NOUNB>
03500 <NOUNB>
03600
03700 <NOUNA>::= FRANCE
03800 AIRPLANE HIJACKING
03900 HIJACKING
04000 CHINA
04100 ISRAEL
04200 MURDER
04300 NIXON
04400 RAPE
04500 RUSSIA
04600 SEX
04700 AIRPLANES
04800 VIETNAM
04900 WAR
05000 THE VIETNAM WAR

```

05100		WATERGATE
05200		THE WATERGATE
05300		
05400	<NOUN>::=	FRANCE
05500		AIRPLANE HIJACKING
05600		HIJACKING
05700		CHINA
05800		ISRAEL
05900		MURDER
06000		NIXON
06100		RAPE
06200		RUSSIA
06300		SEX
06400		AIRPLANES
06500		VIETNAM
06600		WAR
06700		THE VIETNAM WAR
06800		WATERGATE
06900		THE WATERGATE

```

00100  GRAMMAR FOR CHESS
00200
00300  <move>::=      [ <moveb> ]
00400
00500  <moveb>::=      <movea><check-word>
00600                <movea>
00700
00800  <movea>::=      <pce-loc><motion><loca>
00900                <pce-loc><takes><pce-loca>
01000                <castle-move>
01100
01200  <pce-loc>::=   <piece>
01300                <piece> ON <loc>
01400
01500  <loc>::=        <pieceb><square>
01600
01700  <pce-loca>::=  <piecec>
01800                <piecec> ON <loca>
01900
02000  <loca>::=       <pieced><squarea>
02100
02200  <piece>::=      <royal>
02300                <royal><man>
02400                <man>
02500
02600  <man>::=        <bnr>
02700                <bnr> PAWN
02800                PAWN
02900
03000  <pieceb>::=     <royalb>
03100                <royalb><manb>
03200                <manb>
03300
03400  <manb>::=       <bnrb>
03500                <bnrb> PAWN
03600                PAWN
03700
03800  <piecec>::=     <royalc>
03900                <royalc><manc>
04000                <manc>
04100
04200  <manc>::=       <bnrc>
04300                <bnrc> PAWN
04400                PAWN
04500
04600  <pieced>::=     <royald>
04700                <royald><mand>
04800                <mand>
04900
05000  <mand>::=       <bnrd>
05100                <bnrd> PAWN
05200                PAWN
05300
05400  <royal>::=      KING
05500                QUEEN
05600
05700  <bnr>::=        BISHOP
05800                KNIGHT
05900                ROOK
06000

```

06100	<royald>::=	KING
06200		QUEEN
06300		
06400	<bnrd>::=	BISHOP
06500		KNIGHT
06600		ROOK
06700		
06800	<royalb>::=	KING
06900		QUEEN
07000		
07100	<bnrb>::=	BISHOP
07200		KNIGHT
07300		ROOK
07400		
07500	<royalc>::=	KING
07600		QUEEN
07700		
07800	<bnrc>::=	BISHOP
07900		KNIGHT
08000		ROOK
08100		
08200	<square>::=	ONE
08300		TWO
08400		THREE
08500		FOUR
08600		FIVE
08700		SIX
08800		SEVEN
08900		EIGHT
09000		
09100	<squarea>::=	ONE
09200		TWO
09300		THREE
09400		FOUR
09500		FIVE
09600		SIX
09700		SEVEN
09800		EIGHT
09900		
10000	<motion>::=	TO
10100		MOVES-TO
10200		GOES-TO
10300		
10400	<takes>::=	TAKES
10500		CAPTURES
10600		
10700	<castle-move>::=	CASTLE
10800		CASTLE ON <royale> SIDE
10900		CASTLE <royale> SIDE
11000		
11100	<royale>::=	KING
11200		QUEEN
11300		
11400	<check-word>::=	CHECK
11500		MATE



```

00100      BNF FOR THE DOCTOR INTERVIEW. 76 TERMINAL WORDS.
00200
00300      <HEAD>::= [ <SENTENCE> ]
00400
00500      <SENTENCE>::= <INTEROGB> <HABIT-VERB>
00600                <INTEROGC> <SYMPTOM>
00700                <INTEROGD> <SYMPTOM> <AOJ>
00800                <INTEROGE> <SYMPTOMS> <AOJ>
00900                <INTEROGG> <PHYS-CONO>
01000                <INTEROGG> <PERSONAL-STATE>
01100                <INTEROGH> <VERBA> <AILMENT>
01200                <INTEROGH> <VERBB> <PARTICIPIAL>
01300                <U> <INTEROGF> <PARTICIPIAL>
01400                <INTEROGD> <PERSONAL-NOUN> <PERSONAL-ADJ>
01500
01600      <U>::= WHERE
01700            WHEN
01800
01900      <QUANTIFIER>::= OFTEN
02000            LONG
02100            FREQUENTLY
02200            MUCH
02300
02400      <INTEROGA>::= HOW
02500            HOW <QUANTIFIER>
02600
02700      <INTEROGB>::= DO YOU
02800            <INTEROGA> DO YOU
02900
03000      <INTEROGC>::= WHERE IS THE
03100
03200      <INTEROGD>::= IS THE
03300            IS YOUR
03400
03500      <INTEROGE>::= ARE THE
03600            ARE YOUR
03700
03800      <INTEROGF>::= WERE YOU
03900            WERE YOU EVER
04000
04100      <INTEROGG>::= ARE YOU
04200            <INTEROGF>
04300
04400      <INTEROGH>::= HAVE YOU
04500            <INTEROGA> HAVE YOU
04600
04700      <VERBA>::= HAD
04800            EVER HAD
04900
05000      <VERBB>::= BEEN
05100            EVER BEEN
05200
05300      <HABIT-VERB>::= SMOKE
05400            ORINK
05500            OVEREAT
05600            SMOKE <SMOKEY-AOJ>
05700
05800      <SMOKEY-AOJ>::= CIGARETTES
05900            POT
06000            GRASS

```

06100  
06200 <SYMPTOM>::= PAIN  
06300       NUMBNESS  
06400       NAUSEA  
06500       DIZZINESS  
06600       BLEEDING  
06700  
06800 <SYMPTOMS>::= HEADACHES  
06900       PAINS  
07000       CRAMPS  
07100       CHEST PAINS  
07200       LESIONS  
07300  
07400 <AILMENT>::= MUMPS  
07500       MEASLES  
07600       CHICKEN-POX  
07700       TUBERCULOSIS  
07800       ASTHMA  
07900       GONORRHEA  
08000       CLOUDY URINE  
08100       SURGERY  
08200       AN OPERATION  
08300  
08400 <ADJ>::= SEVERE  
08500       MILD  
08600       BAD  
08700       CONTINUOUS  
08800       SHARP  
08900       SERIOUS  
09000  
09100 <PHYS-COND>::= SICK  
09200       ILL  
09300       IN PAIN  
09400       FEVERISH  
09500       DEAD  
09600  
09700 <PERSONAL-STATE>::= AFRAID OF SURGERY  
09800       CASTRATED  
09900  
10000 <PERSONAL-NOUN>::= URINE  
10100       HEAD  
10200  
10300  
10400 <PERSONAL-ADJ>::= CLOUDY  
10500       ATTACHED  
10600  
10700 <PARTICIPIAL>::= HOSPITALIZED  
10800       CIRCUMCISED  
10900       ANESTHETIZED  
11000       CASTRATED  
11100       AFRAID OF SURGERY  
11200       IMMUNIZED  
11300       INJURED  
11400       SERIOUS  
11500

```
00100 <sentence>::= [ <request> ]
00200
00300 <request>::= COMPUTE <func-phr>
00400 USE <param-phr>
00500
00600 <func-phr>::= <function>
00700 <function> USING <param-phr>
00800
00900 <function>::= THE <name> TRANSFORM
01000
01100 <name>::= HILBERT
01200 FOURIER
01300
01400 <param-phr>::= <param-spec>
01500 <param-spec> WITH <param-phr>
01600
01700 <param-spec>::= A LENGTH OF FIVE HUNDRED TWELVE POINTS
01800 A HAMMING WINDOW
```

```

181
182
44
<sentence>::= 1 -1 0
[ 2 181 1
1 1000
<request> 3 -2 1
2 1000
] 4 182 1
11 1000
ENDOF<sentence> 5 -1 1
4 1000
<request>::= 6 -2 1
2 1000
COMPUTE 7 291 1
6 1000
<func-phr> 8 -3 1
7 1000
USE 9 222 1
6 1000
<param-phr> 10 -6 1
9 1000
ENDOF<request> 11 -2 2
17 500
32 500
<func-phr>::= 12 -3 1
7 1000
<function> 13 -4 1
12 1000
<function> 14 -4 1
12 1000
USING 15 252 1
22 1000
<param-phr> 16 -6 1
15 1000
ENDOF<func-phr> 17 -3 2
22 500
32 500
<function>::= 18 -4 2
12 500
12 500
THE 19 156 1
18 1000
<name> 20 -5 1
19 1000
TRANSFORM 21 300 1
26 1000
ENDOF<function> 22 -4 1
21 1000
<name>::= 23 -5 1
19 1000
HILBERT 24 301 1
23 1000
FOURIER 25 299 1
23 1000
ENDOF<name> 26 -5 2
24 500
25 500
<param-phr>::= 27 -6 3
9 333

```

	15	333		
	30	334		
<param-spec>	28	-7	1	
	27	1000		
<param-spec>	29	-7	1	
	27	1000		
WITH 30	251	1		
	44	1000		
<param-phr>	31	-6	1	
	30	1000		
ENDOF<param-phr>	32	-6	2	
	44	500		
	32	500		
<param-spec>:::	33	-7	2	
	27	500		
	27	500		
A 34	1	1		
	33	1000		
LENGTH 35	565	1		
	34	1000		
OF 36	117	1		
	35	1000		
FIVE 37	58	1		
	36	1000		
HUNDRED 38	338	1		
	37	1000		
TWELVE 39	349	1		
	38	1000		
POINTS 40	225	1		
	39	1000		
A 41	1	1		
	33	1000		
HAMMING 42	253	1		
	41	1000		
WINDOW 43	232	1		
	42	1000		
ENDOF<param-spec>	44	-7	2	
	40	500		
	43	500		

```

2
4
135
1 -      0      0 "NULL"      0      900      0
2 -      0      181 [      1      0      900
      1      100
3 -      0      0 "NULL"      1      900      0
      2      1000
4 -      0      182 ]      1      0      900
      23     100
5 -      0      0 "NULL"      1      900      0
      4      1000
6 -      0      0 "NULL"      1      900      0
      2      1000
7 -      0      291 COMPUTE      1      0      900
      6      100
8 K      5      291 COMPUTE      1      0      900
      7      100
9 AH     24     291 COMPUTE      1      0      900
      8      100
10 M     13     291 COMPUTE      1      0      900
      9      100
11 -      0      291 COMPUTE      1      0      900
      10     100
12 P      1      291 COMPUTE      1      0      900
      11     100
13 Y     18     291 COMPUTE      1      0      900
      12     100
14 UW    19     291 COMPUTE      1      0      900
      13     100
15 -      0      291 COMPUTE      1      0      900
      14     100
16 T      3      291 COMPUTE      1      0      900
      15     100
17 -      0      0 "NULL"      1      900      0
      16     1000
18 -      0      222 USE      1      0      900
      6      100
19 Y     18     222 USE      1      0      900
      18     100
20 UW    19     222 USE      1      0      900
      19     100
21 S     10     222 USE      1      0      900
      20     100
22 -      0      0 "NULL"      1      900      0
      21     1000
23 -      0      0 "NULL"      2      900      0
      34     500
      78     500
24 -      0      0 "NULL"      1      900      0
      16     1000
25 -      0      0 "NULL"      1      900      0
      24     1000
26 -      0      0 "NULL"      1      900      0
      24     1000
27 -      0      252 USING      1      0      900
      51     100
28 Y     18     252 USING      1      0      900
      27     100
29 UW    19     252 USING      1      0      900

```



	28	100			
30 S	10	252 USING	1	0	900
	29	100			
31 IH	28	252 USING	1	0	900
	30	100			
32 NX	15	252 USING	1	0	900
	31	100			
33 -	0	0 "NULL"	1	900	0
	32	1000			
34 -	0	0 "NULL"	2	900	0
	51	500			
	78	500			
35 -	0	0 "NULL"	2	900	0
	24	500			
	24	500			
36 -	0	156 THE	1	0	900
	35	100			
37 DH	9	156 THE	1	0	900
	36	100			
38 AX	30	156 THE	1	0	900
	37	100			
39 -	0	0 "NULL"	1	900	0
	38	1000			
40 -	0	300 TRANSFORM	1	0	900
	69	100			
41 T	3	300 TRANSFORM	1	0	900
	40	100			
42 ER	25	300 TRANSFORM	1	0	900
	41	100			
43 AE	26	300 TRANSFORM	1	0	900
	42	100			
44 N	14	300 TRANSFORM	1	0	900
	43	100			
45 -	0	300 TRANSFORM	1	0	900
	44	100			
46 S	10	300 TRANSFORM	1	0	900
	45	100			
47 F	7	300 TRANSFORM	1	0	900
	46	100			
48 AD	22	300 TRANSFORM	1	0	900
	47	100			
49 ER	25	300 TRANSFORM	1	0	900
	48	100			
50 M	13	300 TRANSFORM	1	0	900
	49	100			
51 -	0	0 "NULL"	1	900	0
	50	1000			
52 -	0	0 "NULL"	1	900	0
	38	1000			
53 -	0	301 HILBERT	1	0	900
	52	100			
54 HH	12	301 HILBERT	1	0	900
	53	100			
55 IH	28	301 HILBERT	1	0	900
	54	100			
56 L	17	301 HILBERT	1	0	900
	55	100			
57 -	0	301 HILBERT	1	0	900
	56	100			
58 B	2	301 HILBERT	1	0	900

# Appendix C—EXAMPLES FROM A SIMPLE LANGUAGE

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	57	100			
59 ER	25	301 HILBERT	1	0	900
	58	100			
60 -	0	301 HILBERT	1	0	900
	59	100			
61 T	3	301 HILBERT	1	0	900
	60	100			
62 -	0	299 FOURIER	1	0	900
	52	100			
63 F	7	299 FOURIER	1	0	900
	62	100			
64 AO	22	299 FOURIER	1	0	900
	63	100			
65 ER	25	299 FOURIER	1	0	900
	64	100			
66 IY	29	299 FOURIER	1	0	900
	65	100			
67 EH	27	299 FOURIER	1	0	900
	66	100			
68 IH	28	299 FOURIER	1	0	900
	67	100			
69 -	0	0 "NULL"	2	900	0
	61	500			
	68	500			
70 -	0	0 "NULL"	3	900	0
	21	333			
	32	333			
	76	334			
71 -	0	0 "NULL"	1	900	0
	70	1000			
72 -	0	0 "NULL"	1	900	0
	70	1000			
73 -	0	251 WITH	1	0	900
	135	100			
74 W	16	251 WITH	1	0	900
	73	100			
75 IH	28	251 WITH	1	0	900
	74	100			
76 F	7	251 WITH	1	0	900
	75	100			
77 -	0	0 "NULL"	1	900	0
	76	1000			
78 -	0	0 "NULL"	2	900	0
	135	500			
	78	500			
79 -	0	0 "NULL"	2	900	0
	70	500			
	70	500			
80 -	0	1 A	1	0	900
	79	100			
81 AX	30	1 A	1	0	900
	80	100			
82 -	0	565 LENGTH	1	0	900
	81	100			
83 L	17	565 LENGTH	1	0	900
	82	100			
84 AX	30	565 LENGTH	1	0	900
	83	100			
85 NX	15	565 LENGTH	1	0	900
	84	100			

86 -	0	585 LENGTH	1	0	900
	85	100			
87 F	7	585 LENGTH	1	0	900
	86	100			
88 -	0	117 OF	1	0	900
	87	100			
89 AD	22	117 OF	1	0	900
	88	100			
90 V	8	117 OF	1	0	900
	89	100			
91 -	0	58 FIVE	1	0	900
	90	100			
92 F	7	58 FIVE	1	0	900
	91	100			
93 AA	23	58 FIVE	1	0	900
	92	100			
94 AX	30	58 FIVE	1	0	900
	93	100			
95 V	8	58 FIVE	1	0	900
	94	100			
96 -	0	338 HUNDRED	1	0	900
	95	100			
97 HH	12	338 HUNDRED	1	0	900
	96	100			
98 AH	24	338 HUNDRED	1	0	900
	97	100			
99 N	14	338 HUNDRED	1	0	900
	98	100			
100 -	0	338 HUNDRED	1	0	900
	99	100			
101 D	4	338 HUNDRED	1	0	900
	100	100			
102 ER	25	338 HUNDRED	1	0	900
	101	100			
103 EH	27	338 HUNDRED	1	0	900
	102	100			
104 -	0	338 HUNDRED	1	0	900
	103	100			
105 D	4	338 HUNDRED	1	0	900
	104	100			
106 -	0	349 TWELVE	1	0	900
	105	100			
107 T	3	349 TWELVE	1	0	900
	106	100			
108 W	16	349 TWELVE	1	0	900
	107	100			
109 EH	27	349 TWELVE	1	0	900
	108	100			
110 L	17	349 TWELVE	1	0	900
	109	100			
111 V	8	349 TWELVE	1	0	900
	110	100			
112 -	0	225 POINTS	1	0	900
	111	100			
113 P	1	225 POINTS	1	0	900
	112	100			
114 AD	22	225 POINTS	1	0	900
	113	100			
115 IH	22	225 POINTS	1	0	900
	114	100			

116 N	14	225 POINTS	1	0	900
	115	100			
117 -	0	225 POINTS	1	0	900
	116	100			
118 T	3	225 POINTS	1	0	900
	117	100			
119 S	10	225 POINTS	1	0	900
	118	100			
120 -	0	1 P	1	0	900
	79	100			
121 AX	30	1 A	1	0	900
	120	100			
122 -	0	253 HAMMING	1	0	900
	121	100			
123 HH	12	253 HAMMING	1	0	900
	122	100			
124 AE	26	253 HAMMING	1	0	900
	123	100			
125 M	13	253 HAMMING	1	0	900
	124	100			
126 IH	28	253 HAMMING	1	0	900
	125	100			
127 NX	15	253 HAMMING	1	0	900
	126	100			
128 -	0	232 WINDOW	1	0	900
	127	100			
129 W	16	232 WINDOW	1	0	900
	128	100			
130 IH	28	232 WINDOW	1	0	900
	129	100			
131 N	14	232 WINDOW	1	0	900
	130	100			
132 -	0	232 WINDOW	1	0	900
	131	100			
133 D	4	232 WINDOW	1	0	900
	132	100			
134 OW	21	232 WINDOW	1	0	900
	133	100			
135 -	0	0 "NULL"	2	900	0
	119	500			
	134	500			

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97:	0	0	0	0	0	0	0	0	0	0	0	0
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104:	0	0	0	0	0	0	0	0	0	0	0	0
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107:	0	0	0	0	0	0	0	0	0	0	0	0
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110:	8	34	0	4	0	0	257	34	253	85	63	12
111:	27	20	0	7	0	1	205	58	269	62	143	46
112:	28	25	0	9	0	4	172	62	282	78	170	52
113:	32	33	12	14	0	5	152	64	230	85	191	84
114:	25	46	33	21	7	10	158	72	265	76	164	99
115:	18	50	33	37	16	14	150	108	251	76	117	115
116:	16	61	31	46	22	22	144	100	241	66	159	119
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119:	21	65	34	55	97	34	150	68	246	48	89	108
120:	26	73	41	58	114	44	145	48	226	30	93	103
121:	25	98	48	66	125	54	159	41	175	20	68	95
122:	32	101	48	65	143	57	161	34	196	20	30	91
123:	32	116	42	70	141	56	167	32	146	21	43	99
124:	32	122	54	74	154	58	145	23	141	25	30	107
125:	38	132	36	86	157	53	96	19	191	25	30	105
126:	36	160	40	117	157	52	64	25	149	26	35	92
127:	43	169	47	135	166	58	52	24	116	23	35	86
128:	42	164	46	166	160	60	69	25	91	19	35	81
129:	44	165	46	180	151	66	71	20	74	19	35	80
130:	34	154	53	201	138	63	80	19	77	18	35	69
131:	31	127	62	200	159	65	95	18	40	19	43	67
132:	26	118	66	172	184	66	92	20	59	20	35	65
133:	30	97	57	140	193	58	84	19	118	21	47	62
134:	25	90	65	123	166	54	119	30	147	22	39	51
135:	30	101	78	121	232	54	107	28	68	24	35	41
136:	42	104	90	104	287	56	58	22	38	24	43	32
137:	37	90	90	60	233	42	0	10	192	37	52	30
138:												

154:	0	0	0	0	0	0	0	0	0	0	1	0
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156:	0	0	0	25	9	25	0	89	0	25	60	5
157:	0	3	0	30	43	43	123	96	143	20	97	52
158:	0	7	91	183	111	47	143	75	67	25	60	63
159:	41	27	93	174	63	54	118	59	77	39	56	83
160:	36	27	75	177	97	41	134	52	94	41	48	90
161:	33	49	85	220	47	42	108	69	44	49	51	89
162:	52	60	67	190	62	31	89	62	123	54	43	86
163:	51	68	64	151	81	27	122	51	145	54	35	83
164:	60	89	87	138	47	23	111	54	107	69	43	72
165:	46	92	73	104	29	22	133	49	162	63	55	75
166:	38	78	59	77	42	20	168	60	193	49	73	75
167:	40	66	52	54	25	18	247	88	94	67	104	94
168:	22	58	52	46	32	15	235	89	91	71	149	91
169:	39	51	58	46	0	9	197	92	152	72	122	84
170:	83	55	62	104	0	24	181	52	87	34	72	17
171:	28	48	4	53	0	24	207	57	82	43	76	17
172:	0	14	0	37	0	23	242	42	32	37	105	17
173:	0	5	5	30	0	30	131	70	35	40	115	14
174:	0	0	3	18	0	18	255	62	62	29	137	14
175:	0	0	0	14	0	17	338	63	0	21	138	17
176:	0	4	0	17	0	22	150	53	0	26	151	13
177:	0	11	0	27	11	31	169	35	83	39	135	14
178:	28	28	63	84	60	60	124	86	124	40	65	37
179:	27	12	59	113	84	59	61	78	176	49	65	172
180:	16	13	44	100	68	59	100	88	209	48	114	169
181:	18	17	52	115	71	69	105	93	173	58	76	158
182:	22	17	45	109	75	57	130	65	206	57	85	126
183:	25	19	54	122	79	69	117	51	175	67	81	121
184:	22	17	50	117	80	62	122	32	215	60	89	137
185:	27	17	62	135	76	83	105	38	175	60	77	146
186:	21	16	54	127	70	104	118	38	179	43	97	154
187:	26	18	50	122	66	113	111	51	183	43	85	151
188:	24	21	50	107	70	111	137	52	192	32	77	145
189:	31	29	63	120	107	128	164	60	77	11	64	118
190:	46	37	59	155	186	160	150	42	5	6	56	32
191:	28	63	14	109	215	140	175	51	0	8	35	32
192:	38	71	35	38	178	73	234	43	17	20	60	38
193:	29	67	69	38	137	64	264	60	48	15	67	38
194:	25	70	37	34	138	56	265	53	74	17	80	50
195:	14	52	40	104	88	38	156	53	242	33	92	88
196:	14	59	52	104	59	28	145	46	266	45	77	106
197:	14	51	54	99	56	20	167	36	256	44	100	96
198:	16	53	61	98	58	20	161	40	253	48	80	89
199:	17	56	64	92	71	19	149	39	261	49	72	80
200:	22	70	51	98	57	22	215	39	190	33	81	52
201:	48	114	85	126	55	21	277	34	19	24	43	36
202:	101	238	190	178	0	35	0	17	0	0	18	22
203:	115	238	207	115	0	23	0	7	0	0	18	20
204:	135	279	126	126	0	18	0	0	0	0	18	17
205:	234	375	0	93	0	15	0	0	0	0	13	5
206:	283	264	0	94	0	37	0	0	0	0	13	4
207:	0	147	0	205	0	58	0	0	0	0	13	7
208:	0	135	27	189	0	81	0	0	0	0	9	12
209:	263	115	105	157	0	73	0	0	0	0	13	14
210:	120	76	125	96	149	76	0	4	0	0	35	38
211:	83	80	132	98	213	106	0	2	0	0	39	58
212:	51	94	83	117	161	158	31	8	0	10	63	96
213:	25	61	39	96	111	164	82	66	76	24	92	149



2: JKB2: USE A HAMMING WINDOW OF FIVE HUNDRED TWELVE POINTS

95:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	0	4018
96:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	0	4018
97:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	0	4018
98:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	1	3925
99:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	0	4018
100:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	0	4018
101:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	0	4018
102:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	0	4018
103:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	1	3925
104:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	0	4018
105:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	0	4018
106:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	0	4018
107:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	0	4018
108:	-	1	F	29	K	162	HH	49	V	36	S	41	F	28	2541	4173
109:	Y	84	G	27	D	19	IY	143	D	17	P	12	P	8	15497	19760
110:	Y	84	P	8	D	17	G	27	P	12	IY	143	IY	145	7952	16759
111:	Y	84	D	19	D	17	SH	42	N	65	T	15	IY	143	5772	11438
112:	D	19	Y	84	UW	94	IY	143	SH	42	N	65	T	15	9944	12102
113:	UW	94	N	65	IY	143	D	17	Y	84	IH	141	T	15	7324	8440
114:	IY	143	UW	94	N	65	Y	84	IH	141	D	19	D	17	5798	6052
115:	IY	143	UW	94	N	65	IH	141	UW	86	IH	137	Y	84	4681	8643
116:	UW	94	IY	143	IH	141	N	65	IH	137	IY	142	UW	86	3845	7153
117:	UW	94	IY	143	UW	86	IH	141	IH	137	N	65	IY	142	5069	6603
118:	UW	94	UW	86	IY	143	N	65	IH	137	IH	141	ER	123	3932	8000
119:	UW	86	ER	123	IY	143	UW	94	IH	137	AX	150	N	65	2253	8575
120:	UW	86	ER	123	AX	151	UW	94	IH	137	AX	150	IY	143	3009	5253
121:	AX	151	UW	86	AX	149	AX	147	ER	123	UW	88	UW	91	5418	8832
122:	AX	151	AX	147	UW	88	UW	86	AX	149	ER	123	UW	91	4688	9942
123:	AX	151	UW	91	UW	88	AX	149	AX	147	Y	165	ER	122	5697	7339
124:	UW	91	AX	151	UW	88	AX	149	AX	147	UW	93	ER	122	7379	8207
125:	UW	88	AX	151	UW	93	ER	122	AX	149	L	80	UW	86	13226	15364
126:	UW	88	UW	93	UW	91	AX	149	ER	122	AX	151	L	80	12905	14210
127:	UW	88	UW	93	L	83	L	82	UW	91	V	33	L	81	15452	17811
128:	UW	88	L	82	UW	93	L	83	V	33	AX	154	UW	91	13468	13786
129:	L	82	UW	88	V	33	L	83	UW	93	AX	154	AO	107	9821	15039
130:	L	82	UW	88	AO	107	AX	154	UW	93	V	33	L	83	6763	13411
131:	L	82	AX	154	AO	107	ER	120	V	33	UW	88	L	83	6554	11203
132:	L	82	ER	120	AX	154	UW	88	V	33	UW	91	NX	70	11697	12394
133:	UW	88	UW	91	AX	151	AX	155	AX	149	UW	93	L	82	9854	17034
134:	UW	88	AX	151	AX	149	UW	91	AX	147	UW	93	Y	165	4751	7173
135:	AX	152	ER	120	UW	91	M	55	NX	70	M	53	UW	88	12474	14788
136:	M	55	ER	125	HH	45	M	53	HH	47	AX	152	-	4	13305	14771
137:	L	80	AX	155	AX	151	UW	88	ER	125	HH	45	HH	47	27523	36606
138:	F	30	Y	163	D	20	T	14	L	80	IY	143	D	19	23654	26352
139:	T	14	S	38	S	40	S	39	F	30	D	19	D	20	4633	17775
140:	S	40	T	14	S	38	F	30	D	20	T	13	D	19	2359	20085
141:	S	38	T	14	S	39	S	40	D	19	F	30	D	20	3061	10319
142:	S	40	S	38	T	14	S	39	F	30	D	20	D	19	6336	18190
143:	S	38	S	39	T	14	S	40	D	19	SH	43	T	15	2094	2125
144:	T	14	S	38	S	39	S	40	D	19	F	30	D	20	5596	7138
145:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	50	3578
146:	N	62	-	3	N	59	M	75	N	66	M	52	N	58	10583	20927
147:	DH	37	K	162	HH	50	V	36	HH	49	-	6	D	16	6219	8257
148:	M	78	M	73	AO	107	L	82	M	77	AO	109	L	79	7605	35088
149:	-	1	F	29	K	162	V	36	HH	49	S	41	F	28	2502	6422
150:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	1	3925
151:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	1	3925
152:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	1	3925
153:	-	1	F	29	V	36	S	41	K	162	F	28	HH	49	1	3925

154: - 1	F 29	V 36	S 41	K 162	F 28	HH 49	1	3925
155: - 1	F 29	V 36	S 41	K 162	F 28	HH 49	1	3925
156: HH 49	K 162	F 29	F 28	S 41	- 1	V 36	3294	4596
157: D 17	D 18	G 27	N 65	ER 123	IH 137	T 13	10583	16399
158: AX 154	AX 149	ER 161	EH 160	HH 48	UH 88	AE 167	19735	21255
159: EH 160	AX 149	ER 161	UH 88	AE 167	L 82	AX 154	16568	16827
160: AX 149	UH 88	ER 161	AX 154	EH 160	AE 167	UH 93	11725	13214
161: EH 160	L 82	AO 107	AX 154	AE 167	L 83	ER 161	13564	17812
162: UH 88	UH 93	AX 149	AX 146	L 82	AE 167	OW 99	15823	16402
163: UH 88	AX 149	UH 93	AX 146	IH 138	AX 151	OW 104	8406	9933
164: NX 71	UH 88	AX 149	UH 93	L 83	IH 138	L 82	13955	14970
165: AX 150	AX 149	UH 88	N 65	IH 138	IY 144	UH 86	16371	16522
166: N 65	AX 150	UH 86	IY 143	IH 137	IY 144	UH 94	8937	9525
167: IY 145	N 65	Y 164	D 17	IH 137	N 60	P 9	17482	20199
168: N 65	D 17	P 9	IH 137	Y 164	UH 94	K 23	16857	21880
169: N 65	D 17	IH 137	UH 94	Y 84	IH 141	IY 143	4580	12643
170: M 56	NX 71	IY 145	Y 85	N 65	D 17	IY 144	17914	18212
171: D 17	IY 145	Y 164	HH 44	K 23	D 18	P 9	13998	14116
172: HH 44	Y 164	K 23	G 26	K 24	N 60	D 18	3777	5781
173: K 23	HH 44	D 18	T 13	F 28	HH 49	D 17	6377	11433
174: Y 164	HH 44	K 24	K 23	P 9	D 18	D 17	5728	6684
175: Y 164	G 26	N 60	HH 44	K 24	K 23	P 9	5068	8557
176: K 23	HH 44	D 18	T 13	Y 164	F 28	P 9	3642	5194
177: D 18	HH 44	K 23	D 17	P 9	T 13	K 24	3706	9799
178: P 10	AX 149	UH 88	ER 123	N 65	AX 151	IH 137	15215	17662
179: AX 146	OW 104	AE 129	IH 139	EH 131	UH 90	AE 126	7513	7652
180: IH 137	EH 131	AE 130	UH 86	UH 90	AE 129	OW 104	6898	8550
181: OW 104	AE 129	AX 146	IH 137	UH 90	AE 130	EH 131	5756	6098
182: UH 86	AX 146	IH 137	UH 90	OW 104	ER 123	AE 129	7652	7678
183: AX 146	OW 104	AE 129	IH 137	AX 149	UH 90	UH 86	6166	8021
184: AX 146	UH 90	UH 86	OW 104	IH 137	AE 129	ER 123	6955	9923
185: AX 146	OW 104	AE 129	UH 90	OW 99	AH 113	AX 149	3821	5458
186: UH 90	OW 104	AX 146	AE 129	AH 113	OW 99	AH 118	4743	5058
187: AX 146	OW 104	UH 90	AE 129	AH 113	OW 99	AH 118	4273	4320
188: UH 90	AX 146	OW 104	AE 129	AH 113	ER 122	AX 149	4224	5914
189: ER 161	AE 128	AH 113	AX 149	AX 154	UH 91	OW 104	6313	6855
190: ER 120	HH 48	V 31	AX 154	HH 46	AX 153	AX 152	7025	13314
191: ER 120	AX 152	M 54	UH 91	V 31	AX 154	HH 48	12881	17683
192: M 54	Y 165	N 63	UH 91	AX 152	NX 70	AX 147	3206	6964
193: M 54	Y 165	AX 147	UH 91	N 63	M 56	NX 69	6987	8007
194: Y 165	M 54	AX 147	UH 91	AX 151	N 63	NX 69	5986	9524
195: UH 86	ER 123	AX 150	IH 137	UH 94	AX 151	IY 143	6422	10170
196: AX 150	UH 86	IY 143	IH 137	ER 123	UH 94	IH 138	8861	9177
197: IY 143	AX 150	UH 86	UH 94	N 65	IH 137	ER 123	10383	10483
198: AX 150	UH 86	IY 143	N 65	IH 137	UH 94	ER 123	9717	10855
199: UH 86	AX 150	IY 143	ER 123	N 65	UH 94	IH 137	11045	11239
200: IY 144	N 65	AX 150	P 12	AX 151	AX 149	D 17	11088	13978
201: NX 68	M 56	N 60	NX 69	M 54	NX 71	AX 154	5191	12991
202: V 32	N 64	W 76	W 74	N 59	- 3	W 75	5832	7241
203: N 64	V 32	W 74	W 76	- 3	N 61	N 59	2503	12900
204: V 32	N 64	N 61	N 58	W 75	N 59	- 3	9646	14177
205: - 2	N 61	N 58	W 75	M 51	N 62	V 32	3266	34473
206: - 2	N 62	N 58	W 75	M 51	N 66	V 32	12574	18834
207: W 78	OH 37	V 35	P 11	N 59	L 82	L 83	380	19873
208: W 78	OH 37	V 35	P 11	L 82	L 83	N 59	2535	14098
209: - 3	W 75	N 59	W 74	N 62	V 32	W 76	7743	9905
210: V 34	HH 47	ER 125	L 81	- 4	V 31	AX 148	4227	8393
211: HH 47	ER 125	V 34	- 4	L 81	HH 45	HH 46	2035	2938
212: HH 46	ER 124	ER 120	AX 153	V 31	HH 47	AX 155	9803	10147
213: AE 128	ER 161	ER 122	OW 104	AH 113	UH 96	AH 118	6678	9896

AP News Retrieval Task:

Let me have all the stories.  
Let me have all the stories.

Give me France.  
Give me France.

Tell me all about Nixon.  
Tell me all about Nixon.

Tell me about Watergate.  
Tell me about Watergate.

Tell us all about China.  
Tell us all about China.

Give us Russia.  
Give us Russia.

Tell me all about Israel.  
Tell me all about Israel.

Let me have the headlines.  
Let me have the headlines.

Give me the summary.  
Give me the summary.

Interactive formant tracking task:

I want to do formant tracking.

I want to do formant tracking.

Use a Hamming window with five hundred, twelve points.

Use a Hanning window to five hundred, four points.

Increment the window in steps of one hundred points.

Increment the window in steps of one hundred points.

For each window, compute the fast Fourier transform.

For each window, compute the fast Fourier transform.

Display the Fourier spectrum.

Display the Fourier spectrum.

Display the LPC smoothed spectrum.

Display the LPC smoothed spectrum.

Display the cepstrally smoothed spectrum.

Display the cepstrally smoothed spectrum.

Use a pre-emphasis of six db per octave.

Use a pre-emphasis of sixty db per octave.

Medical questionnaire task:

Do you smoke?

Do you smoke?

Do you drink?

Do you drink?

Do you have numbness?

Is your numbness?

Where is the pain?

Where is the pain?

Have you had mumps?

Is your numbness?

Are your headaches severe?

Are your headaches severe?

Are you in pain?

Are you in pain?

Where were you hospitalized?

Where were you hospitalized?

When were you immunized?

When were you immunized?

Have you been circumcised?

Have you been circumcised?

Is the pain severe?

Is the pain severe?

Have you ever been anesthetized?

Have you ever been anesthetized?

Have you ever been injured?

Have you ever been injured?

Have you ever had an operation?

Have you ever had an operation?

How often do you have nausea?

How often have you had an operation?

How long have you had asthma?

How long have you had asthma?

Is your dizziness continuous?  
Is your dizziness continuous?

Are you afraid of surgery?  
Are you afraid of surgery?

How much do you weigh?  
How much do you smoke?

Is your urine cloudy?  
Is your urine cloudy?

Were you ever hospitalized?  
Were you ever hospitalized?

Voice chess task:

Pawn goes to king four.  
Pawn goes to king four.

Knight moves to king bishop three.  
Knight moves to king bishop three.

Bishop goes to bishop four.  
Bishop goes to bishop four.

Knight on king bishop three goes to knight five.  
Knight on king bishop three goes to king five.

Pawn captures pawn.  
Pawn captures pawn.

Knight on king knight five captures pawn on king bishop seven.  
Knight on king knight five captures pawn on king bishop seven.

Queen goes to bishop three.  
Queen goes to bishop three.

Knight goes to bishop three.  
Knight pawn goes to bishop three.

Knight captures knight on queen five.  
Knight captures knight on pawn four.

King to queen one.  
King to queen one.

Knight takes pawn.  
Knight takes pawn.

Knight captures rook on queen rook eight.  
Knight captures rook on queen rook two.

Queen goes to queen five.  
Queen goes to queen five.

Pawn on queen two goes to queen four.  
Pawn on queen two goes to queen four.

Bishop moves to knight five, check.  
Bishop moves to knight five, check.

Bishop goes to knight five, check.  
Bishop goes to knight five, check.



Queen on queen five captures queen, check.  
Queen on queen one captures queen, check.

Queen moves to queen five, check.  
King moves to queen five, check.

Queen takes bishop on queen six.  
Queen takes bishop on queen six.

Rook moves to king one.  
Rook moves to king one.

Rook moves to king seven, check.  
Pawn moves to king seven, check.

Queen moves to queen bishop seven.  
Queen moves to queen bishop seven.

## Interactive formant tracking task:

I want to do formant tracking.

I want to do formant tracking.

Use a Hamming window of five hundred twelve points.

Use a Hamming window of five hundred points.

Use utterance number six of file number five.

Use utterance number six of file number five.

Increment the window in steps of one hundred points.

Increment the window in steps of four points.

For each window, display the Fourier spectrum.

For each window, display the formant tracks.

Compute the LPC smoothed spectrum using the autocorrelation method.

Compute the LPC smoothed spectrum using the autocorrelation method.

Compute the roots of the inverse filter using Balzertow's method.

Compute the roots of the inverse filter using Balzertow's method.

Display the imaginary part of the roots.

Display the imaginary part of the roots.

I want to compare the autocorrelation method with the covariance method.

I want to compare the autocorrelation method and the covariance method.

Increment the window by one hundred points.

Increment the window by one points.

Display the FFT spectrum.

Display the FFT spectrum.

Use a Hanning window of two hundred, fifty-six points.

Use a Hanning window of two hundred, six hertz.

Display the FFT spectrum.

Display the FFT spectrum.

Compute the Hilbert transform.

Use two points.

I want to look at image enhancement with different parameters.

I want to compare image enhancement with different parameters.

Display the spectrogram with a pre-emphasis of six decibels per octave.

Display the spectrogram to a pre-emphasis of six thousand five hertz.

Use a ceiling of thirty with a floor of zero.  
Use a ceiling of ten to a floor of zero.

For each utterance display the spectrogram.  
For each utterance display the spectrogram.

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